Three Essays in Asset Pricing

Dissertation
submitted to the
Faculty of Business, Economics and Informatics
of the University of Zurich

to obtain the degree of
Doktor der Wirtschaftswissenschaften, Dr. oec.
(corresponds to Doctor of Philosophy, PhD)

presented by

Dominic Burkhardt
from Fisibach, AG

approved in February 2015 at the request of

Prof. Dr. Henrik Hasseltoft
Prof. Dr. Thorsten Hens

The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, 11.02.2015

The Chairman of the Doctoral Board: Prof. Dr. Josef Zweimüller

Acknowledgements

First of all, I am very much obliged to my supervisor Prof. Dr. Henrik Hasseltoft, a man not only representing excellence in research, but also in personality. Henrik, I thank you for your guidance throughout my Ph.D. studies, for your valuable advice, encouragement, patience, support, and for countless insightful discussions - not only about finance and economics, but also about politics and other things. It was a major honor to have the opportunity to work with you and to learn from you.

I would also like to express my deep gratitude to my co-supervisor, Prof. Dr. Thorsten Hens. Thorsten, long ago your lectures and your extensive knowledge sparked my interest in finance, and it was your encouragement and support that motivated me to start a Ph.D. program in finance. I thank you for opening this door, for your encouragement and fairness, and for your intellectual and financial support.

I am also deeply grateful to Prof. Dr. Alexandre Ziegler; an incredibly intelligent, friendly and knowledgeable person. Alexis, I thank you for all the stimulating discussions, for the insights into economics and finance you provided me, for the kickbox-fights, etc.. My sincere thanks and appreciation also to my co-author Nilu and to my colleagues and friends Gabriel Neukomm, Manish Gupta and Kristoph Streikert. Thanks for many interesting discussions, lunches and dinners.

Finally, the greatest thanks are due to my family and my beloved girlfriend Fabienne. I am deeply indebted to my parents Renate and Heinz and to my sister Anina for their support and their faith in me. I am incredibly grateful to Fabienne for supporting me in every moment and situation. Thank you for having made all this possible.

This thesis is dedicated to my good old friend Fabian Schwager and to all the other loved ones I have lost along the way.

Financial Support by the Swiss Finance Institute and the Swiss National Science Foundation is gratefully acknowledged.

Zürich, September 2014 Dominic Burkhardt

Contents

Part I

Introduction

Introduction and Summary of Research Results

Asset pricing is one of the main areas in Finance and aims at understanding and explaining what drives the prices of claims to future payments. How do the prices of assets fluctuate and why do they behave in the way we observe? This dissertation consists of three articles addressing practically relevant topics in the broad field of asset pricing. More specifically, the three research papers constituting this dissertation (i) show how the correlation of growth and inflation varies over time and how this affects stock-bond correlations and the relation between inflation and asset prices, (ii) establish that the way inflation risk is priced in the cross-section of individual stocks is closely related to the cyclicality of inflation[1], and (iii) find that the relation between mass media coverage and the cross-section of stock returns varies across countries and depends on whether the market state is good or bad.

The first research paper, "***Understanding Asset Correlations***", starts with the observation that the correlation between the returns on U.S. stocks and nominal government bonds has varied substantially over time. From being predominantly positive since the 1960's, the correlation turned sharply negative in the early 2000's. We then provide new empirical evidence showing that stock-bond correlations are inversely related to the correlation between real growth and inflation: Stock-bond correlations are positive (negative) when inflation is countercyclical (procyclical).[2] The large shift from positive to negative stock-bond correlations around 2000, for example, coincided with inflation turning procyclical after having been countercyclical for several decades.

We also provide new empirical evidence showing that not only macro and asset correlations

[1] Inflation is defined to be procyclical (countercyclical) if the correlation between inflation and measures of real economic activity, such as e.g. real consumption growth, real GDP growth oor industrial production growth, is positive (negative).

[2] This also holds for correlations between dividend yields and nominal yields (the so-called Fed-model).

switched sign in the early 2000's, but also several other relations between inflation and asset prices. In particular, while we find that an increase in inflation risk always depresses equity prices, the relation between equity prices and the level of expected inflation sharply changed from negative to positive around 2000. On the other hand, we document that an increase in inflation risk depresses (increases) prices of nominal bonds when inflation is countercyclical (procyclical), while the relation between bond prices and expected inflation is always negative. We also find that inflation risk predicts stock-bond correlations positively in the countercyclical inflation period 1965-2000, but negatively in the procyclical inflation period 2000-2011. Overall, we observe that all these relations switch sign at the same time, namely around 2000, and line up with a contemporaneous switch in the correlation of growth and inflation, from negative to positive. This suggests that the cyclicality of inflation seems to have important asset pricing implications and that expected inflation and inflation risk seem to be important drivers of equity and bond returns.

We rationalize our empirical findings in a long-run risk model framework. The model is based on Bansal and Yaron (2004), but we introduce two novel features that are crucial to our results and well-supported by data. First, we introduce non-neutral inflation shocks affecting future real economic growth. This allows inflation to have a direct impact on real asset prices and on equity and bond risk premia, which both vary with inflation risk. Second, we introduce a regime-switching mechanism that allows for counter- and procyclical inflation regimes. The calibrated model is able to qualitatively match all our empirical results. In particular, it matches the changing asset and macro correlations we observe in data while matching a range of key macro and asset-price moments. The model can also produce an upward-sloping real yield curve and rationally explains the so-called Fed-model.

In the model, the market price of inflation risk is negative (positive) when inflation is countercyclical (procyclical). The impact of positive shocks to expected inflation on real aggregate equity returns is negative (positive) when inflation is countercyclical (procyclical)[3], implying low (high) equity returns in bad (good) times. Consequently, inflation shocks make equity pro-

[3]Via a cash-flow channel in the model: Positive inflation shocks imply higher (lower) future growth when inflation is procyclical (countercyclical), which feeds into higher (lower) future aggregate dividend growth, causing higher (lower) current returns.

cyclical and agents ask a positive equity risk premium for bearing inflation risk in both inflation regimes.

On the other hand, an increase in the level of expected inflation represents a cash-flow effect on nominal bonds and is always bad for nominal bond returns and raises nominal yields, while it lowers (raises) real yields in the countercyclical (procyclical) regime. This implies that inflation shocks make nominal bonds procyclical (countercyclical) if inflation is countercyclical (procyclical). Hence, nominal bond risk premia load positively (negatively) on inflation risk when inflation is countercyclical (procyclical). Real bond risk premia, however, load negatively on inflation risk in both regimes since real bonds always provide a hedge against bad times.

These mechanisms also explain why and how stock and bond returns (and dividend yields and nominal yields) comove. Changes in inflation risk move bond and equity risk premia into the same direction when inflation is countercyclical but in opposite directions when inflation is procyclical, since nominal bonds then provide insurance against bad times while equity is still risky. Hence, inflation uncertainty can produce both positive and negative stock-bond correlations depending on the inflation regime.

In the second research paper, ***Time-Varying Inflation Risk and the Cross-Section of Stock Returns***, I pick up the observation that the cyclicality of inflation varies over time and relate it to the time-variation of inflation risk premiums in the cross-section of individual equities, hereby positing a rational explanation for how and why inflation risk in the cross-section of stock returns changes over time.

I provide empirical evidence indicating that the way inflation risk is priced in the cross-sections of U.S. and UK stocks is closely related to whether the economy is in a pro- or countercyclical inflation state. Employing three different out-of-sample signals that indicate whether the economy is in a pro- or countercyclical inflation regime, I empirically show that the market price of inflation risk is positive (negative) in the cross-section of U.S. and UK stocks when inflation is procyclical (countercyclical). As a consequence, risk premiums on stocks with positive/negative exposure to inflation shocks depend on whether inflation is pro- or countercyclical. When inflation is countercyclical, positive inflation shocks are suggestive of bad economic times and the market price of inflation risk is negative. Stocks with a highly positive (negative) exposure to inflation shocks yield high (low) real returns during inflationary times, are hence countercyclical (procyclical) and consequently command a negative (positive) inflation risk premium on average. If inflation is procyclical on the other hand, positive inflation shocks indicate good economic times and the market price of inflation risk is positive. Hence, stocks with a highly positive (negative) exposure to inflation shocks that yield high (low) real returns during inflationary times are subject to a positive (negative) inflation risk premium. This implies that a zero-investment strategy that goes long low (high) inflation-beta stocks and short high (low) inflation-beta stocks when inflation is countercyclical (procyclical) should yield positive returns on average.

The returns resulting from implementing this zero-investment strategy confirm that inflation risk in equity markets is closely related to the cyclicality of inflation. Whereas a zero-investment strategy that is always long low and short high inflation-beta stocks experiences major losses during procyclical inflation periods, employing the three out-of-sample signals allows anticipating switches in the cyclicality of inflation in due time, such that the signal-based strategies are able to transform these losses into gains and consequently yield positive average returns over pro-, as well as over countercyclical inflation periods. In the U.S. and the UK, the signal-based strategies yield statistically highly significant and economically large average returns, even after controlling for well-known risk factors. This implies that inflation risk seems to be an important component of risk premiums in the cross-section of U.S. and UK equities that cannot be explained by widely accepted risk factors.

In the third research paper contained in this dissertation, ***Media-Coverage, the Cross-Section of Stock Returns and Market States: An International Study***, we analyze the relation between mass media coverage and the cross-section of stock returns in 20 financially developed stock markets around the world. The starting point of this article is the finding by Fang and Peress (2009) that stocks not covered by mass media earn significantly higher future returns than stocks that are highly covered by mass media (the so-called media effect). Employing a new measure of mass media coverage also comprising internet news sources, considering a more recent and longer time period and a larger set of U.S. stocks, we find U.S. results that are qualitatively similar to those of Fang and Peress (2009): Stocks neglected by mass media earn a statistically significant and economically important return premium compared to stocks highly covered by mass media.

We expand the analysis to an international level by analyzing the entire stock markets in 19 major European and Asia-Pacific (APAC) countries. We employ 12 years of mass media data on more than $21'000$ companies and document considerable differences as to the magnitude and direction of the media effect in countries outside the U.S. Despite the effect being positive in the majority of countries, only seven countries (Hongkong, France, Switzerland, Spain, the Netherlands, Belgium and Austria) display positive no-media premiums that are statistically significant and economically large. In the UK we find a large and significant negative no-media premium; returns monotonically increase with media coverage. Despite these heterogeneous country-results, we show that a positive media effect consistently exists and is particularly strong in most countries among small and illiquid stocks. Hence, the role of mass media seems to be particularly important for these subsets of stocks, which arguably are characterized by rather poor information dissemination.

As our main contribution, we relate the media effect to a simple measure of the state of the market. Defining the market state in a country as good/bullish (bad/bearish) when the fraction of stocks with positive returns in a month is above (below) 50%, we show that in the overwhelming majority of countries, portfolios containing stocks that are not covered by mass media during good market state months subsequently clearly outperform portfolios containing stocks that are highly covered during good market state months. Hence, there is a positive, mostly economically large no-media premium, when we condition on the market state being positive. Conditional on the market state being bad on the other hand, we find much smaller and mostly insignificant or negative no-media premiums. Utilizing this insight, we show that a strategy that goes long stocks not covered and short those highly covered by mass media when the market state is positive, and the opposite when the market state is negative, yields a positive return premium in 16 out of 20 countries. The premiums are mostly statistically significant, especially among the countries with the largest stock market capitalizations in our sample. For these countries, the return premiums are significant and economically large for holding periods up to 12 months and stable across various subgroups of stocks.

REFERENCES

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Fang, L., and J. Peress, 2009, Media coverage and the cross-section of stock returns, *Journal of Finance* 64, 2023—-2052.

Part II

Research Papers

Understanding Asset Correlations

Dominic Burkhardt* Henrik Hasseltoft

Abstract

We document an inverse relation between stock-bond correlations and correlations of growth and inflation. We find that rising inflation uncertainty lowers stock prices but can either raise or lower nominal bond prices depending on the inflation regime. We explain our findings in a long-run risk model with non-neutral inflation shocks and regime shifts, allowing for countercyclical and procyclical inflation regimes. The model can produce an upward-sloping real yield curve and rationally explains the so-called Fed-model. Finally, we document that inflation and monetary policy shocks were important drivers of stock-bond correlations during the countercyclical period 1965-2000, while output shocks dominated during the procyclical period 2000-2011.

Keywords: fed-model, inflation, long-run risks, regime-switching, stock-bond correlation

*We would like to thank Ravi Bansal, Magnus Dahlquist, Jerome Detemple, Peter Lochte Jorgensen, Christian Julliard, Christian Schlag, Peter Schotman, Romeo Tedongap, Stijn Van Nieuwerburgh and seminar participants at BI Oslo, HEC Paris, the Institute for Financial Research (SIFR), Stockholm School of Economics, Tilburg University, University of Zurich, the 2009 North American Summer Meeting of the Econometric Society in Boston, the 2010 Inquire Europe meeting in Berlin, the 2012 Eastern Finance Association meeting in Boston, the 2012 Symposium on time-varying correlation and volatility in Wolverhampton, the 2012 FINRISK meeting in Gerzensee, the 2012 EFMA meeting in Barcelona, the 2012 EFA meeting in Copenhagen, and the 2012 Money, Macro, and Finance conference in Dublin for helpful comments. Financial support from Bankforskningsinstitutet is gratefully acknowledged.

1 Introduction

The unconditional correlation between returns on US stocks and nominal government bonds has been close to zero in post-war data but has varied substantially over time as shown in Figure 1. From being positive throughout most of the pre-2000 period, correlations turned sharply negative in the early 2000's. We document that these changes in asset correlations coincide with changes in several other relations between inflation, inflation uncertainty, and asset prices. We provide new empirical evidence showing that these shifts are related to changes in the cyclical nature of inflation. The main point of our paper is to show how the correlation of growth and inflation varies over time and how this affects the relation between inflation and asset prices and stock-bond correlations.

We estimate a regime-switching model on real consumption growth, inflation, stock, and bond excess returns for the period 1965-2011 and find a significant inverse relation between stock-bond correlations and correlations of growth and inflation. Stock-bond correlations are positive in times of stagflation but negative when inflation and growth are positively correlated. In particular, the large shift around 2000 when stock-bond correlations turned sharply negative coincided with inflation turning procyclical after having been countercyclical for several decades. Figure 2 exemplifies this inverse relation by plotting stock-bond correlations against correlations between inflation and different measures of economic growth.[1]

We also provide new evidence showing that the effect of inflation uncertainty on stock-bond correlations can be both positive and negative depending on the inflation regime. We find that inflation uncertainty predicted stock-bond correlations positively in the countercyclical inflation period 1965-2000, but negatively in the procyclical inflation period 2000-2011. While the effect of inflation uncertainty on stock prices was negative throughout our sample period, its impact on nominal bond prices switched sign from negative to positive around 2000. We believe this is a novel finding suggesting that inflation uncertainty lowers nominal bond prices when inflation is countercyclical but raises bond prices when inflation is procyclical. We do not claim that

[1]Correlations are based on quarterly data and computed for non-overlapping five-year periods. Our inflation measure uses the price index for nondurables and services provided by the Bureau of Economic Analysis. Our results are robust to using the Consumer Price Index and the Core-Consumer Price Index which means our findings are not driven by volatile food or energy prices.

inflation uncertainty is the only driver of stock-bond correlations.[2] However, we believe it is an important factor since it can produce both positive and negative stock-bond correlations.

We also contribute to the literature on the comovement of nominal yields and dividend yields, often named the Fed-model.[3] We find that also the correlation of dividend yields and nominal yields is inversely related to the correlation of growth and inflation. Figure 3 exemplifies this. From being positively correlated 1965-2000, correlations of dividend yields and nominal yields turned sharply negative in the early 2000's at the same time as inflation turned procyclical. Since nominal yields move with inflation, this suggests that the relation between equity valuations and inflation has changed considerably over time and seems to coincide with changes in the cyclical nature of inflation.

So is there a plausible economic story for the empirical observations described above? Yes. Theory suggests that nominal bonds are risky when inflation is countercyclical, since it implies procyclical returns, but provide a hedge against bad times when inflation is procyclical. An increase in inflation risk should therefore raise bond risk premia and yields in the first case while lowering risk premia and yields in the second case. Equity risk premia should load positively on inflation risk if inflation is bad for growth and equity returns, producing procyclical stock returns. The same holds if inflation is positively associated with growth and stock returns since high inflation then coincides with low marginal utility of investors and high stock returns. Equity risk premia should therefore load positively on inflation risk while nominal bond risk premia and yields can load negatively or positively depending on the cyclical state of inflation. We find empirical support for this in data.

Our empirical findings suggest that expected inflation and inflation volatility are important drivers of both equity and bonds. We therefore choose to rationalize our findings using the long-run risk framework since it emphasizes time-varying macroeconomic expectations and volatilities. The main setup follows Bansal and Yaron (2004), but we introduce two novel features that are crucial for our results and well-supported by data. First, inflation shocks are assumed to be non-neutral, affecting real growth. Inflation therefore has a direct impact on real asset prices and

[2]For example, Baele et al. (2010) find that liquidity factors play an important role.
[3]See for example Ritter and Warr (2002), Campbell and Vuolteenaho (2004), Cohen et al. (2005), and Bekaert and Engstrom (2010).

on equity and bond risk premia which both vary with inflation volatility. Second, we introduce a regime-switching mechanism that allows for countercyclical and procyclical inflation regimes. This implies that inflation can be associated with both bad and good economic times in the model. Both, equity and bonds are risky in the countercyclical regime which makes equity and bond risk premia move positively with inflation volatility, producing positive stock-bond correlations. However, equity and bond risk premia are negatively related in the procyclical regime as nominal bonds act as a hedge while stocks are still risky. This generates negative stock-bond correlations. The same mechanism also allows the model to produce switching correlations between dividend yields and nominal yields. Overall, the model matches the changing asset and macro correlations we observe in data while being consistent with a range of unconditional macro and asset-price moments.

Interestingly, the theoretical model can produce an upward-sloping real term structure in contrast to traditional long-run risk models.[4] In a single-regime model, the average slope is determined by the average risk premium. With multiple regimes, however, expectations of future short rates also matter for the average slope. For example, standing in a low-short rate regime, the "expectations part" of the yield curve is positive as long as there is a non-zero probability of jumping to a high-short rate state. Short rates were low in the procyclical period 2000-2011 but high in the countercyclical period 1965-2000. The model therefore implies a positive (negative) expectations part of the real yield curve post 2000 (pre 2000). Risk premiums on real bonds are negative in both regimes but the positive expectation part outweighs the negative risk premium post 2000. Hence, the model generates a positively sloped real yield curve for the 2000-2011 period. This is different from existing long-run risk models which generate a downward-sloping real yield curve since the slope is exclusively determined by the negative real bond risk premia.[5]

Identifying the source behind changes in macro and asset correlations is an important question. We estimate a VAR model of inflation, real output growth, the Federal funds rate, and the stock-bond covariance for the two sub-periods pre 2000 and post 2000. We impose a simple

[4]The real yield curve has been upward sloping in the US. However, real bonds only started trading in 1997 so the sample period is short and the market was initially highly illiquid. Long-term evidence from UK real bonds suggest a downward-sloping real yield curve (e.g., Piazzesi and Schneider, 2006).
[5]Eraker et al. (2011) generate an upward sloping real yield curve in a long-run risk framework through a different channel by introducing durable consumption good risk.

recursive orthogonalization scheme using the Cholesky factorization in order to interpret shocks to the Federal funds rate as structural monetary policy shocks. We find that shocks to inflation and monetary policy were important drivers of stock-bond covariances during the countercyclical period 1965:1-1999:4 while output shocks clearly dominated during the procyclical period 2000:1-2011:4. Hence, the relative magnitude of nominal versus real shocks in the economy seems to be an important determinant of the different regimes.

While early contributions focussed on unconditional stock-bond correlations (e.g., Shiller and Beltratti, 1992, and Campbell and Ammer, 1993), the focus has shifted towards understanding conditional correlations. Connolly et al. (2005) document that a rise in stock market uncertainty predicts stock-bond correlations negatively. Baele et al. (2010) find that macro factors have limited success in explaining the time-varying stock-bond correlation. Campbell et al. (2010) estimate a quadratic term-structure model with latent state variables of which one captures the covariance between inflation and the real pricing kernel. They identify this state variable through the observed stock-bond covariance and describe how it impacts bond risk premia. The authors provide a nice intuition for how the cyclicality of inflation might affect the riskiness of nominal bonds. However, it is never actually shown using fundamental data whether there exist different inflation regimes in data and whether such regimes line up with different regimes in stock-bond correlations. David and Veronesi (2009) explore the role of learning about inflation and real earnings for the variance and covariance of stock and bond returns. Their model is successful in predicting second moments of returns and emphasizes cash flow effects and uncertainty about the current state of the economy while keeping market prices of risk constant.[6]

In contrast to these papers, we provide several new pieces of empirical evidence that highlight the impact of a changing covariance between growth and inflation on asset prices. For example, we explicitly estimate changes in the cyclicality of inflation from data and link it to asset prices. We show how the different inflation regimes determine how inflation uncertainty impacts asset prices and how this can explain the changing asset correlations. Furthermore, we motivate our findings using a consumption-based equilibrium model which means asset prices are directly tied to fundamental macro factors such as consumption growth and inflation.

[6]See also Bekaert et al. (2010) who discuss stock-bond correlations in an external-habit framework.

The so called Fed-model refers to the, on average, positive relation between dividend yields and nominal yields in post-war data. The positive relation has puzzled many observers. Why should a real variable, like the dividend yield, move with nominal interest rates? Since nominal rates rise with inflation, inflation must be negatively related to real dividend growth rates and/or positively associated with expected equity returns in order to explain a positive dividend yield-nominal yield correlation. Virtually all papers in this literature rule out a rational explanation for the link between inflation and dividend yields and rely instead on inflation illusion in which irrational investors basically discount real cash flows with nominal discount rates (Modigliani and Cohn, 1979).[7] An increase in inflation raises discount rates and lowers stock prices, producing a positive correlation between dividend yields and nominal yields. However, this is inconsistent with the large negative correlations observed post 2000 and during the 1930's. This raises questions about the validity of the inflation illusion explanation. Instead, we provide a rational explanation based on the changing effects of inflation uncertainty on stocks and bonds stemming from the time-varying relation between growth and inflation. Our theoretical model matches the large shifts in correlations observed in data.

This paper is also related to the vast literature on stock returns and inflation. An incomplete list includes Fama (1981), Geske and Roll (1983), Stulz (1986), Kaul (1987), Marshall (1992), and Boudoukh (1993).[8] Recently, Bekaert and Wang (2010) study the relation between inflation and stock returns across a large number of countries and find evidence of predominantly negative inflation betas. More generally, we build on the literature of pricing stocks and bonds in equilibrium using the recursive preferences of Epstein and Zin (1989) and Weil (1989) (e.g., Campbell, 1993, 1996, 1999, Duffie et al., 1997, and Restoy and Weil, 1998). Related papers that use the long-run risk framework are Piazzesi and Schneider (2006), Eraker (2008), Bansal and Shaliastovich (2010), and Hasseltoft (2012).[9]

[7]A notable exception is Bekaert and Engstrom (2010) who argue that rational mechanisms are at work and ascribe the positive correlation between dividend yields and nominal yields to the large incidence of stagflation in US data. They document a positive relation between expected inflation and proxies for the equity risk premium.

[8]Note that Fama's so called proxy hypothesis is distinct from this paper since we stress the link between inflation and risk premiums rather than inflation and cash flows.

[9]Our paper is also related to the literature on regime-switching models in equity and bond markets. For example, Cecchetti et al. (1990), Ang and Chen (2002), Bibkov and Chernov (2008), Lettau et al. (2008), Constantinides and Ghosh (2011) study regime-switching models for equities while Hamilton (1988), Gray (1996), Evans (1998), Ang and Bekaert (2002b, 2002c), Bansal and Zhou (2002), Bansal et al. (2004), Dai et al. (2007), and Ang et al. (2008) all study bond markets. Ang and Bekaert (2002a) and (2004) study asset allocation in a regime-

Our article proceeds as follows. Section 2 describes our data and provides new empirical evidence. Section 3 rationalizes our empirical findings using a long-run risk model that incorporates non-neutral inflation shocks and a regime-switching mechanism allowing for both counter- and procyclical inflation regimes. Section 4 describes the calibration of the theoretical model and its implications for a range of unconditional macro and asset-price moments. Section 5 describes in detail implications for bond risk premia, slope of the term structure, equity risk premia, and asset correlations in the model. Section 6 estimates shocks to inflation, output, and monetary policy and studies how they impact stock-bond covariances. Section 7 concludes. Details on the theoretical model and additional empirical results are presented in the Appendix.

2 Empirical Analysis

2.1 Data

Quarterly aggregate US consumption data for the period 1965:1-2011:4 and annual data for the period 1930-2011 on nondurables and services is collected from the Bureau of Economic Analysis. Real consumption growth and inflation are computed as in Piazzesi and Schneider (2006) using the price index that corresponds to the consumption data. Value-weighted market returns (NYSE/AMEX) are retrieved from CRSP. Nominal interest rates and bond returns are collected from the Fama-Bliss files in CRSP. Price-dividend ratios are formed by imputing dividends from monthly CRSP returns that include and exclude dividends (see e.g. Bansal et al., 2005). Quarterly dividends D_t are formed by summing monthly dividends. Due to the strong seasonality of dividend payments, we use a four-quarter moving average of dividend payments, $\bar{D}_t = \frac{D_t+D_{t-1}+D_{t-2}+D_{t-3}}{4}$. Real dividend growth rates are found by taking the log first difference of $\bar{D}_t$ and deflating using the constructed inflation series. Data on industrial production and real GDP are obtained from the St. Louis FRED database and from GlobalFinancialData respectively.

switching framework.

2.2 Empirical Evidence

The introduction of the paper provided motivating examples for the inverse relation between asset and macro correlations found in data. Table I reports the actual correlation coefficients between growth, inflation, and asset returns. Motivated by the preceding figures, we choose to break the sample in two parts, prior to and after 2000.[10] The table shows that inflation and growth were negatively correlated prior to 2000, -0.42, but comoved positively thereafter, 0.30. The correlations between stock and bond returns also underwent a significant change, from 0.28 pre 2000 to -0.63 thereafter. Interestingly, the correlation between inflation and stock returns also changed from -0.20 to 0.27 after 2000. Overall, this suggests that several relations switched around year 2000; inflation turned procyclical, stock-bond correlations turned sharply negative and equity switched to act as an inflation hedge.

In Table II, we formally test whether the difference in unconditional correlation coefficients pre and post 2000 are statistically significant using a Jennrich (1970) test. We consider four different correlation matrices; macro variables and asset returns jointly, only macro variables, only asset returns, and only stock returns and inflation. The table shows that we can clearly reject the null hypothesis of equal correlation coefficients across subsamples for all specifications. It has been argued in the literature that simply splitting the sample ex-post is not a perfectly reliable method for identifying regime switches as it might lead to a selection bias (e.g., Boyer et. al, 1999, and Chesnay and Jondeau, 2001). We therefore, later in this section, estimate a regime-switching model that explicitly allows us to formally identify breaking points between countercyclical and procyclical inflation regimes.

To further validate the inverse relation between macro and asset correlations, we take a long-term perspective by considering annual consumption growth and inflation starting in 1930 in Figure 4. Visual inspection suggests that the comovement between inflation and growth has varied considerably. In particular, the 1930's experienced a strong positive comovement, as The Great Depression was associated with low growth coupled with deflation. The positive correlation was further exacerbated by the strong rebound in growth and inflation starting in

[10]We estimate a more formal breaking point later in this section.

1933. In contrast, the US economy underwent a stagflationary period in the 1970's and early 1980's. Growth and inflation started to comove positively again around the year 2000.

Figure 5 computes 10-year correlations between growth and inflation and between dividend yields and inflation for the period 1930-2011.[11] First, the graph quantifies the considerable variation in the cyclicality of inflation. From a correlation of 0.80 in the 1930's, correlations reached -0.80 during the 1970's and were then close to 0.60 in the 2000's. Second, the graph indicates a clear inverse relation between macro correlations and correlations of dividend yields and inflation for this extended time period.

We also provide new evidence showing that not only macro and asset correlations switched sign in the early 2000's but also several other relations between inflation and asset prices. Figure 6 shows that the relation between the level of expected inflation and price-dividend ratios switched sharply from negative to positive around 2000.[12] This is in line with our earlier finding that stock returns were positively related to inflation post 2000. This stands in contrast to the common finding that stocks are a poor inflation hedge. Interestingly, the same figure shows that inflation risk has been negatively related to price-dividend ratios throughout the entire sample period.[13] Hence, stock prices seem to respond differently to changes in the level of inflation and changes in inflation risk. The model we present later provides a rational explanation for this phenomenon.

Table III reports results from regressing log price-dividend ratios onto expected inflation and inflation risk for the full sample and for the two subsamples. First, the two variables explain a large part of the variation in price-dividend ratios with R^2s around 50%. Second, the regression coefficient for expected inflation switches sign to positive in the procyclical state, albeit not statistically significant.[14] Third, inflation risk is consistently negatively related to price-dividend ratios with a high statistical significance. Hence, the table suggests that while the relation between equity-valuation ratios and the level of inflation may changes sign, an

[11]Since interest rates were not market determined prior to the Treasury-Fed accord in 1951, we choose to focus on the relation between equity and inflation as opposed to using bond returns or interest rates.

[12]Expected inflation is measured as the fitted value from projecting quarterly inflation onto lagged growth, inflation, and yield spread.

[13]Inflation risk is measured as the dispersion of inflation forecasts based on the GDP price deflator. The Appendix shows that our general results are robust to using the dispersion of inflation forecasts based on CPI or the conditional volatility of inflation estimated from a GARCH(1,1) model.

[14]Adding expected consumption growth and consumption risk to the regression results in a coefficient for expected inflation that switches sign to *significantly* positive in the procyclical state, see Table IV.

increase in inflation risk always depresses equity prices.

Conventional wisdom suggests that an increase in inflation risk should raise nominal yields and affect bond returns negatively. Figure 7 shows that this is not always true. In fact, inflation risk and nominal interest rates were *negatively* correlated during the periods 1985-1990 and 2000-2011. We believe this is a novel finding and raises the question of what the underlying mechanism is. The answer is, as discussed above, that the riskiness of nominal bonds depends on whether inflation is counter- or procyclical. Since nominal bonds are risky assets in periods of countercyclical inflation, their returns will suffer in periods of high inflation risk. Conversely, nominal bonds provide a hedge against bad times when inflation is procyclical. This makes their returns positively related to inflation risk. Table V supports these findings by reporting results from regressing the 5-year nominal interest rate onto expected inflation and inflation risk. We find that the regression coefficient for inflation risk is significantly positive in the countercyclical inflation regime but switches sign to significantly negative in the procyclical state.[15] This finding is robust to adding expected consumption growth and consumption risk to the regression, see Table VI.

Consistent with our finding that inflation risk affects asset prices differently depending on the inflation regime, we find that inflation risk predicts stock-bond correlations positively when inflation is countercyclical but negatively when inflation is procyclical. Table VII reports results from regressing quarterly stock-bond covariances onto lagged inflation risk. While it has been documented elsewhere that inflation volatility predicts the stock-bond covariance positively (e.g. Viceira, 2010), we are not aware of any paper showing that this relation can switch sign.

To formally analyze the relation between macro variables and asset returns and to identify potential regime switches, we estimate a two-state Markov-switching (MS) model. We assume that quarterly real consumption growth, inflation, excess stock returns, and excess bond returns follow a one-lag vector autoregression:

[15]This result does not depend on the maturity of the bond and is robust to using a different measure of expected inflation as control variable in the form of the long-run mean of inflation, as shown in the Appendix. Borrowing from the literature on adaptive learning, this measure is computed as $\frac{\sum_{i=0}^{t-1} v^i \pi_{t-i}}{\sum_{i=0}^{t-1} v^i}$ where v is set equal to 0.98 and where we consider a backward looking period of 40 quarters. Similar results are also obtained when using inflation expectations from Survey of Professional Forecasters.

$$Y_{t+1} = \mu(s_{t+1}) + \beta(s_{t+1})Y_t + \epsilon_{t+1}, \tag{1}$$

where $Y_{t+1} = [\Delta c_{t+1}, \pi_{t+1}, r_{s,t+1}, r_{b,t+1}]'$, $\epsilon_{t+1} \sim N(0, \Omega(s_{t+1}))$ and where the regime s_{t+1} is presumed to follow a two-state Markov chain with transition probabilities $p_{ij} = P(s_{t+1} = j|s_t = i)$. The probability of ending up in tomorrow's regime $s_{t+1} = (0,1)$ given today's regime $s_t = (0,1)$ is governed by the transition probability matrix of a Markov chain:

$$P = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix},$$

where $\sum_{j=0}^{1} p_{ij} = 1$ and $0 < p_{ij} < 1$.

Stock returns refer to the NYSE/AMEX portfolio available from CRSP and bond returns refer to the 5 to 10-year US Treasury Fama bond portfolio also obtained from CRSP. All variables are observed quarterly. The companion matrix β, the μ matrix and the variance-covariance matrix Ω are assumed to follow the same Markov chain process, yielding two possible states in total.[16]

The estimation results are reported in Table VIII. There are three key takeaways from this table. First, the effect of inflation on future growth (element (1,2) in β) and the covariance between growth and inflation shocks (element (1,2) in Ω) both switch from negative to positive in the second state. Although estimates for the second state are subject to rather large standard errors, the numbers are consistent with the fact that the correlation between growth and inflation turned positive in the second state. Second, the covariance between shocks to stock and bond returns changed even more dramatically from positive to negative in the second state (element (3,4) in Ω), where both covariance terms are statistically significant. This is consistent with our earlier evidence that correlations between stocks and bonds turned sharply negative in the early 2000's. Third, the covariance between shocks to inflation and stock returns (element (2,3) in Ω) switched from negative to positive in the second state, consistent with our earlier evidence that stocks seem to have provided an inflation hedge throughout the 2000's. In Tables IX

[16] The setup follows Hamilton (1989,1994) among others. We have estimated various MS-VAR specifications allowing for a larger number of states, more lags in the VAR, etc.. We have also elaborated with time-varying transition probabilities. They all yield similar qualitative conclusions.

and X we report that the unconditional correlation coefficients for the two regimes implied by our estimated Markov-switching model are close to data and that Jennrich (1970) tests of these implied correlations suggest we can reject the null hypothesis of equal unconditional correlations across subsamples.

The transition probabilities, p_{11} and p_{22}, are estimated to 0.977 and 0.939. This implies unconditional probabilities of 0.73 and 0.27 for being in the counter- versus procyclical state. The estimated probabilities imply a longer expected duration for the countercyclical state, 43 quarters, versus 16 quarters for the procyclical inflation state.[17] Next, we test the null hypothesis that the conditional correlations implied by the $\Omega(s_{t+1})$-matrices of our estimated Markov-switching model are constant, $\rho(s_{t+1} = 0) = \rho(s_{t+1} = 1)$, across regimes using a Likelihood Ratio test. Our system with four variables yields six restricted correlation coefficients. Table XI reports that we can clearly reject the null of constant conditional correlations across regimes.

Using our estimation results we compute the implied probability of being in the procyclical regime at each time t. We consider both filtered regime probabilities that use information up to time t and smoothed regime probabilities that use information from the entire sample. The probabilities are plotted in Figure 8. We find that a large part of the sample period is dominated by the countercyclical state. We find a temporary jump to the procyclical state in the late 1980's and then a more long-lasting move to a procyclical state in the early 2000's. Large opposite shocks to growth and inflation in the fourth quarter of 2007 explain the large drop in smoothed probabilities at the end of the sample. However, a large deflationary shock together with a sharp drop in growth in the fourth quarter of 2008 explains the reversal in probabilities. We find that the smoothed probability exceeds 0.50 in the second quarter of 2001, wherefore we treat this as the formally estimated breaking point between the two inflation regimes.

Next, we compute for each time t the conditional correlations of growth and inflation and of stock and bond returns implied by the estimated regime-switching model and plot them in Figure 9.[18] First, the relative movements of the two lines suggest a clear inverse relation, particulary in

[17]Considering two states, i and j, the unconditional probability of being in state j is computed as $\frac{1-p_{ii}}{2-p_{jj}-p_{ii}}$. The expected duration of state i is computed as $\frac{1}{1-p_{ii}}$.

[18]The conditional correlations are based on the covariance matrix $Cov(Y_{t+1}|I_t)$ that is implied by the regime-switching VAR given in equation (1).

the late 1980's, the early 2000's, and recently around the financial crisis. Second, the absolute movements of the correlations are also consistent with our earlier evidence that macro and asset correlations underwent a significant shift in the early 2000's.

Overall, we have shown that a number of relations between inflation and asset prices have switched sign over time. Our evidence suggests that the switches in signs all occurred at the same time, namely around 2000. We have shown that these observations line up with a contemporaneous switch in the correlation of growth and inflation, from negative to positive.

3 A Long-Run Risk Model with Switching Inflation Regimes

This section presents a consumption-based equilibrium model with a representative agent that provides a rational explanation for our empirical findings while matching a range of important macro and asset-price moments. The model builds on the so-called long-run risk literature which relies on Epstein and Zin (1989) and Weil (1989) recursive preferences, persistent macro shocks, and time-varying macroeconomic volatility. The original long-run risk model of Bansal and Yaron (2004) relies on persistent shocks to expected consumption growth, which together with recursive preferences produces sizeable equity risk premia. Inflation plays no role in that model.

In contrast, this paper focusses on long-run shocks to inflation and their effect on growth and asset prices. The model contains two additional key features compared to the standard long-run risk model: First, long-run inflation shocks are non-neutral and impact real economic growth directly. This allows inflation to have a direct impact on the real pricing kernel and therefore on both, equity and bond risk premia. As a result, expected returns on equity and bonds vary with the conditional variance of inflation. Second, we incorporate a Markov-switching regime mechanism that allows the relation between real growth and inflation to switch sign. This allows the model to produce both a counter- and procyclical inflation regime. We find these ingredients to be crucial for explaining the switching relations between inflation and asset prices in general and between stock and bond returns in particular. In general, we find that these two main distinctions from the original long-run risk model open up a range of novel asset-pricing implications.

3.1 Macro Dynamics

Let $\Delta c_{t+1}, \pi_{t+1}$, Δd_{t+1}, and $\sigma^2_{\pi,t+1}$ denote the logarithmic consumption growth, inflation, dividend growth, and the conditional variance of inflation respectively. Let μ_c, μ_π, and μ_d denote the unconditional means and let x_c and x_π denote the time-varying parts of the conditional means. We consider an economy subject to regime-shifts between two possible states. Tomorrow's regime is denoted $s_{t+1} = (0, 1)$ and the probability of ending up in tomorrow's regime given today's regime $s_t = (0, 1)$ is governed by the transition probability matrix of a Markov chain:

$$P = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix},$$

where $P(s_{t+1} = j|s_t = i) = p_{ij}$, $\sum_{j=0}^{1} p_{ij} = 1$ and $0 < p_{ij} < 1$. We assume that agents are able to observe the current regime.

We assume the following macro dynamics:

$$\Delta c_{t+1} = \mu_c(s_{t+1}) + x_{c,t} + \sigma_c \eta_{c,t+1}, \tag{2}$$

$$\pi_{t+1} = \mu_\pi(s_{t+1}) + x_{\pi,t} + \sigma_{\pi,t} \eta_{\pi,t+1}, \tag{3}$$

$$\Delta d_{t+1} = \mu_d + \phi x_{c,t} + \varphi \sigma_c \eta_{d,t+1}, \tag{4}$$

$$\sigma^2_{\pi,t+1} = \sigma^2_\pi + v_\pi \left(\sigma^2_{\pi,t} - \sigma^2_\pi\right) + \sigma_\nu w_{t+1}, \tag{5}$$

$$\begin{pmatrix} x_{c,t+1} \\ x_{\pi,t+1} \end{pmatrix} = \begin{pmatrix} \beta_1(s_{t+1}) & \beta_2(s_{t+1}) \\ 0 & \beta_4(s_{t+1}) \end{pmatrix} \begin{pmatrix} x_{c,t} \\ x_{\pi,t} \end{pmatrix} + \begin{pmatrix} \delta_1(s_{t+1}) & \delta_2(s_{t+1}) \\ \delta_3(s_{t+1}) & \delta_4(s_{t+1}) \end{pmatrix} \begin{pmatrix} \sigma_c \varepsilon_{c,t+1} \\ \sigma_{\pi,t} \varepsilon_{\pi,t+1} \end{pmatrix}, \tag{6}$$

where all shocks are uncorrelated, i.i.d. normally distributed with a mean of zero and a variance of one. The β and δ matrices plus μ_c and μ_π depend on tomorrow's regime $s_{t+1} = (0, 1)$. We set element (2,1) in β equal to zero for parsimonious and tractability reasons. This does not affect our qualitative findings. We keep the volatility parameters and the dividend growth parameters constant across regimes since we are mainly interested in the interaction between growth and inflation.

The presence of regime-shifts, inflation, and inflation volatility are new compared to the specification in Bansal and Yaron (2004). While the process for dividend growth is identical to the original long-run risk model, the specification for realized and expected growth in Bansal and Yaron (2004) using our notation would be: $\Delta c_{t+1} = \mu_c + x_{c,t} + \sigma_c \eta_{c,t+1}$ and $x_{c,t+1} = \beta_1 x_{c,t} + \delta_1 \sigma_c \varepsilon_{c,t+1}$.

The volatility of inflation $\sigma^2_{\pi,t+1}$ varies over time and gives rise to time-varying risk premiums as shown in Section 5.[19] The notion of heteroscedasticity in inflation is a well established empirical fact; early contributions include Engle (1982) and Bollerslev (1986). The state variables of the model are consequently $x_{c,t}$, $x_{\pi,t}$, and $\sigma^2_{\pi,t}$. The conditional means of consumption growth and inflation are related through β_2 which means that expected inflation feeds into future expectations of growth. β_2 allows real bonds and price-dividend ratios, in addition to nominal bonds, to be functions of expected inflation. Furthermore, β_2 creates a direct link between expected inflation and the real pricing kernel which means that inflation affects both bond and equity risk premiums. Since β_2 is subject to regime shifts, it can take on both positive and negative values which is important for matching the changing growth-inflation and asset correlations we observe in data.

This is the most parsimonious specification that allows the model to match both unconditional and conditional macro and asset-price moments. By restricting a number of parameters to be constant across regimes we make it harder for the model to match the data. One could of course relax several of the restrictions. For example, we could allow for a non-zero β_3, i.e. an interaction between $x_{c,t}$ and $x_{\pi,t+1}$. We could allow dividend growth parameters, volatility parameters, or the entire variance-covariance matrix of growth and inflation to vary with time. Hasseltoft (2009) contains some of these relaxations. Overall, giving more flexibility to the model does not change our main qualitative results.

[19]The typical long-run risk specification relies on time-varying volatility of consumption growth. For parsimonious reasons, we have restricted time-variation in second moments to inflation since our focus is mainly on the impact of inflation on asset prices.

3.2 Investor Preferences

The representative agent in the economy has Epstein and Zin (1989) and Weil (1989) recursive preferences:

$$U_t = \left\{ (1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta (E_t[U_{t+1}^{1-\gamma}])^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}}, \tag{7}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, $\gamma \geq 0$ denotes the risk aversion coefficient and $\psi \geq 0$ the elasticity of intertemporal substitution (EIS). The discount factor is represented by δ. This preference specification allows time preferences to be separated from risk preferences. This stands in contrast to time-separable expected utility in which the desire to smooth consumption over states and over time are interlinked. The agent prefers early (late) resolution of risk when the risk aversion is larger (smaller) than the reciprocal of the EIS. A preference for early resolution and an EIS above one imply that $\theta < 1$. This specification nests the time-separable power utility model for $\gamma = \frac{1}{\psi}$ (i.e., $\theta = 1$).

The agent is subject to the budget constraint $W_{t+1} = R_{c,t+1} (W_t - C_t)$, where the agent's total wealth is denoted W_t, $W_t - C_t$ is the amount of wealth invested in asset markets and $R_{c,t+1}$ denotes the gross return on the agent's total wealth portfolio. This asset delivers aggregate consumption as its dividends each period.

Following Epstein and Zin (1989) plus acknowledging the presence of regime-shifts, the logarithm of the stochastic discount factor (SDF) can be written as:

$$m_{t+1}(s_{t+1}) = \theta \ln(\delta) - \frac{\theta}{\psi} \Delta c_{t+1} - (1-\theta)\, r_{c,t+1}(s_{t+1}), \tag{8}$$

where $\ln(R_{c,t+1}) = r_{c,t+1}$. Note that the SDF depends on both consumption growth and on the return from the total wealth portfolio. Recall that $\theta = 1$ under power utility, which brings us back to the standard time-separable SDF.

3.3 Solving the Model

Returns on the aggregate wealth portfolio and the market portfolio are approximated as in Campbell and Shiller (1988):

$$r_{c,t+1}(s_{t+1}) = k_{c,0} + k_{c,1} pc_{t+1}(s_{t+1}) - pc_t(s_t) + \Delta c_{t+1}, \tag{9}$$

$$r_{m,t+1}(s_{t+1}) = k_{d,0} + k_{d,1} pd_{t+1}(s_{t+1}) - pd_t(s_t) + \Delta d_{t+1}, \tag{10}$$

where pc_t and pd_t denote the log price-consumption ratio and the log price-dividend ratio.[20] The constants k_c and k_d are functions of the average level of pc_t and pd_t, denoted $\bar{pc}$ and $\bar{pd}$.[21]

3.4 Solving for Equity

All asset prices and valuation ratios are conjectured to be functions of the time-varying conditional means of consumption growth and inflation plus the time-varying conditional variance of inflation. Starting with the log price-consumption ratio, it is conjectured to be a linear function of the state variables as follows:

$$pc_t(s_t) = A_{c,0}(s_t) + A_{c,1}(s_t)x_{c,t} + A_{c,2}(s_t)x_{\pi,t} + A_{c,3}(s_t)\sigma^2_{\pi,t}. \tag{11}$$

The regime dependence of the coefficients plus the existence of $A_{c,2}$ and $A_{c,3}$ are new compared to Bansal and Yaron (2004). $A_{c,2}(s_t)$ and $A_{c,3}(s_t)$ arise from the fact that inflation has a direct impact on real economic growth through $\beta_2(s_t)$ and $\delta_2(s_t)$. In order to analytically solve for the A-coefficients we make use of the macro dynamics, the law of iterated expectations, and of the Euler equation for the consumption asset. The Appendix describes in detail how we solve the model and contains analytical expressions for the A-coefficients. The expression for $A_{c,1}(s_t)$ collapses to the same expression as in Bansal and Yaron (2004) should we restrict the model to a single regime.

[20] Bansal et al. (2007a) show that the approximate analytical solutions for the returns are close to the numerical solutions and deliver similar model implications.

[21] Specifically, the constants are $k_{c,1} = \frac{\exp(\bar{pc})}{1+\exp(\bar{pc})}$ and $k_{c,0} = \ln(1 + \exp(\bar{pc})) - k_{c,1}\bar{pc}$ and similarly for the k_d coefficients.

$A_{c,1}(s_t)$ is positive whenever the elasticity of intertemporal substitution (EIS) is greater than one, implying a positive relation between expected growth and asset prices in both regimes. $A_{c,2}(s_t)$ represents the loading of the price-consumption ratio on expected inflation. Its sign depends mainly on $\beta_2(s_t)$ and on the EIS. For $\beta_2(s_t) < 0$, high inflation signals negative growth and will therefore depress the price-consumption ratio, i.e., $A_{c,2}(s_t) < 0$. The opposite holds when $\beta_2(s_t) > 0$ as high inflation then signals positive growth and therefore higher price-consumption ratios, $A_{c,2}(s_t) > 0$. This only holds when the EIS exceeds one, meaning that the intertemporal substitution effect dominates the wealth effect. Therefore, higher expected inflation lowers price-consumption ratios in times of stagflation but raises them when inflation is procyclical. In the case of expected utility ($\frac{1}{\psi} = \gamma$), a risk aversion coefficient above one implies that the wealth effect dominates, which results in a positive value of $A_{c,2}(s_t)$ when $\beta_2(s_t) < 0$. This is counterfactual since it implies rising asset prices in times of stagflation which is opposite to what we observe in data. $A_{c,3}(s_t)$ is negative in both regimes given a high value of the EIS, indicating a negative relation between price-consumption ratios and inflation volatility. As uncertainty about growth is bad for stock prices in Bansal and Yaron (2004), uncertainty about inflation is bad for stocks in our specification.

In order to understand how macro shocks affect asset prices we consider the innovations to the real pricing kernel. To do so, we take expectations using the information set $I_t = \{x_{c,t}, x_{\pi,t}, \sigma^2_{\pi,t}, s_t\}$, which means that the state tomorrow s_{t+1} is uncertain:

$$
\begin{aligned}
m_{t+1}(s_{t+1}) - E[m_{t+1}(s_{t+1})|I_t] &= -\lambda_{\eta_c}\sigma_c\eta_{c,t+1} - \lambda_{\varepsilon_c}(s_{t+1})\sigma_c\varepsilon_{c,t+1} - \lambda_{\nu}(s_{t+1})\sigma_\upsilon w_{t+1} \\
&\quad -\lambda_{\varepsilon_\pi}(s_{t+1})\sigma_{\pi,t}\varepsilon_{\pi,t+1} + V(s_t, s_{t+1}) \qquad (12) \\
\lambda_{\eta_c} &= \gamma \\
\lambda_{\varepsilon_c}(s_{t+1}) &= (1-\theta)[k_{c,1}A_{c,1}(s_{t+1})\delta_1(s_{t+1}) + k_{c,1}A_{c,2}(s_{t+1})\delta_3(s_{t+1})] \\
\lambda_{\nu}(s_{t+1}) &= (1-\theta)k_{c,1}A_{c,3}(s_{t+1}) \\
\lambda_{\varepsilon_\pi}(s_{t+1}) &= (1-\theta)[k_{c,1}A_{c,1}(s_{t+1})\delta_2(s_{t+1}) + k_{c,1}A_{c,2}(s_{t+1})\delta_4(s_{t+1})],
\end{aligned}
$$

where the λ's represent market prices of risk and where the expression for $V(s_t, s_{t+1})$ arises because tomorrow's state is uncertain as of time t. We report the actual expression for $V(s_t, s_{t+1})$

plus detailed derivations in the Appendix.

The first two sources of risk are the same as in Bansal and Yaron (2004), namely short run consumption risk and long-run consumption risk which both exhibit positive market prices of risk across regimes. The third shock term reflects shocks to inflation volatility which have a negative price of risk ($\lambda_{\nu}(s_{t+1}) < 0$) regardless of the economic regime. Hence, the representative agent dislikes higher inflation uncertainty in all states of the world. In contrast to existing long-run risk specifications, long-run inflation shocks are priced which makes up the last shock term in Equation (12). A negative value of $\lambda_{\varepsilon_{\pi}}(s_t)$ implies that the representative agent dislikes positive shocks to expected inflation and therefore requires a positive risk premium on assets that perform badly in periods of high inflation. Note that $\lambda_{\varepsilon_{\pi}}(s_t)$ can switch sign depending on the regime. It is negative in times of stagflation and positive when inflation is procyclical. Recall that $\theta = 1$ under power utility, which means that long-run inflation risk is not priced and that the only source of priced risk left is short-run consumption risk λ_{η_c}. Overall, long-run inflation shocks represent an additional risk premium part in the economy compared to models in which only consumption shocks are priced.

The log price-dividend ratio is also conjectured to be a linear function of the three state variables:

$$pd_t(s_t) = A_{d,0}(s_t) + A_{d,1}(s_t)x_{c,t} + A_{d,2}(s_t)x_{\pi,t} + A_{d,3}(s_t)\sigma^2_{\pi,t}. \tag{13}$$

The coefficients are solved for in an analogous manner to the A_c coefficients. The Appendix describes the derivations in detail and reports the full analytical expressions. Again, the expression for $A_{d,1}(s_t)$ collapses to the expression in Bansal and Yaron (2004) should we restrict the model to a single-regime economy. $A_{d,2}(s_t)$ and $A_{d,3}(s_t)$ are new compared to existing long-run risk models and determine the impact of the level of inflation and inflation volatility on equity prices.

Expected consumption growth and price-dividend ratios are positively associated for high values of the EIS, meaning that $A_{d,1}(s_t) > 0$ in both regimes. $A_{d,2}(s_t)$ is in general negative when the EIS is above one and when inflation is bad for future growth $\beta_2(s_t) < 0$. This means that high expected inflation depresses equity valuation ratios in periods of countercyclical inflation. In periods of procyclical inflation, $\beta_2(s_t)$ is positive which switches the sign of $A_{d,2}(s_t)$ to positive. This mechanism allows the model to match the switching relation between price-dividend ratios and inflation levels found in data, as was shown in Figure 6 and Table III.

A rise in inflation volatility has a negative impact on price-dividend ratios ($A_{d,3}(s_t) < 0$) in both regimes provided a high value of the EIS. While the relation between price-dividend ratios and the level of inflation can switch sign in the model, a rise in inflation uncertainty is always bad news for equity valuations. This arises since inflation shocks always contribute to procyclical stock returns in the model regardless of the inflation regime. Hence, equity is always risky with respect to inflation shocks. This is consistent with Figure 6 and Table III showing a negative relation between price-dividend ratios and inflation risk in data throughout the entire sample period.

3.5 Solving for Real Bonds

The log price of a real bond with a maturity of n periods is conjectured to be a function of the same state variables as before:

$$q_{t,n}(s_t) = D_{0,n}(s_t) + D_{1,n}(s_t)x_{c,t} + D_{2,n}(s_t)x_{\pi,t} + D_{3,n}(s_t)\sigma^2_{\pi,t}. \tag{14}$$

Let $y_{t,n} = -\frac{1}{n}q_{t,n}$ denote the n-period continuously compounded real yield. Then:

$$y_{t,n}(s_t) = -\frac{1}{n}(D_{0,n}(s_t) + D_{1,n}(s_t)x_{c,t} + D_{2,n}(s_t)x_{\pi,t} + D_{3,n}(s_t)\sigma^2_{\pi,t}), \tag{15}$$

where the D-coefficients determine how yields respond to changes in expected consumption growth, expected inflation, and inflation volatility. The Appendix shows how we solve for the coefficients and reports the corresponding expressions.

For plausible parameter values, real yields increase in response to higher expected consumption growth ($D_{1,n}(s_t) < 0$). Consumption shocks therefore generate countercyclical bond returns and contribute to negative risk premiums on real bonds. Real yields decrease in response to higher inflation when inflation is bad news for growth, resulting in a positive $D_{2,n}(s_t)$ coefficient. In this case, inflation shocks also contribute to negative expected returns since they generate positive bond returns in bad inflationary times. This is consistent with earlier studies such as Fama and Gibbons (1982), Pennacchi (1991), and Boudoukh (1993). Ang et al. (2008) also document a negative relation between real rates and expected inflation but find the correlation to be positive for longer horizons. In the procyclical inflation regime, real yields instead move positively with inflation ($D_{2,n}(s_t) < 0$). Hence, the model can accommodate changes in the relation between real interest rates and inflation by accounting for changes in the cyclical nature of inflation.

An increase in inflation uncertainty lowers real yields ($D_{3,n}(s_t) > 0$), with long rates dropping more than short rates. This occurs because inflation risk moves real bonds through a discount-rate channel. When inflation is considered bad news for growth, inflation shocks lower real yields as discussed above and therefore generate high bond returns in bad times. If inflation instead is positively related to growth, inflation shocks raise real yields, generating poor bond returns in good times. In both cases, inflation shocks contribute to countercyclical returns and therefore to a negative risk premium on real bonds. Hence, a rise in inflation volatility is always associated with lower real yields regardless of the prevailing regime.

3.6 Solving for Nominal Bonds

Nominal log bond prices are conjectured to be functions of the same state variables:

$$q^{\$}_{t,n}(s_t) \quad = \quad D^{\$}_{0,n}(s_t) + D^{\$}_{1,n}(s_t)x_{c,t} + D^{\$}_{2,n}(s_t)x_{\pi,t} + D^{\$}_{3,n}(s_t)\sigma^2_{\pi,t}. \tag{16}$$

Let $y^{\$}_{t,n} = -\frac{1}{n}q^{\$}_{t,n}$ denote the n-period continuously compounded nominal yield. Then:

$$y^{\$}_{t,n}(s_t) \quad = \quad -\frac{1}{n}(D^{\$}_{0,n}(s_t) + D^{\$}_{1,n}(s_t)x_{c,t} + D^{\$}_{2,n}(s_t)x_{\pi,t} + D^{\$}_{3,n}(s_t)\sigma^2_{\pi,t}), \tag{17}$$

where the $D^{\$}$-coefficients determine how nominal yields respond to changes in expected consumption growth, inflation, and inflation volatility. Solving for nominal log bond prices requires the use of the nominal log pricing kernel which is determined by the difference between the real log pricing kernel and the inflation rate:

$$m^{\$}_{t+1}(s_{t+1}) = m_{t+1}(s_{t+1}) - \pi_{t+1}. \tag{18}$$

The Appendix shows how to solve for the coefficients and reports the detailed expressions.

The response of nominal yields to changes in expected growth is the same as for real yields, meaning that $D^{\$}_{1,n}(s_t) < 0$ in both states for reasonable parameter values. This means that shocks to consumption growth contribute to negative risk premiums also for nominal bonds. As expected, nominal yields move positively with expected inflation, implying a negative value of $D^{\$}_{2,n}(s_t)$. This holds regardless of the economic state and reflects a cash-flow effect on nominal bonds. Hence, while real yields may decrease or increase in response to expected inflation depending on the current cyclical state, nominal yields always rise with the level of inflation.

The effect of inflation volatility on yields depends on whether inflation is counter- or procyclical and reflects a discount-rate channel stemming from inflation risk. When inflation is negatively (positively) correlated with growth, higher inflation will raise yields through the cash-flow channel and generate poor bond returns in bad (good) times. Hence, nominal bonds may be subject to either countercyclical or procyclical returns and can therefore constitute both a risky asset or a hedging asset with respect to inflation risk. A rise in inflation risk can therefore be associated with both higher or lower yields through its different effect on bond risk premia. This means that $D^{\$}_{3,n}(s_t)$ can be either negative or positive depending on the inflation regime. This is the key mechanism that allows the model to match the switching relation between nominal interest rates and inflation uncertainty documented in data. We elaborate further on the link between inflation risk and bond risk premia in Section 5.

4 Calibration of Model

Motivated by the estimated breaking point in our empirical regime-switching model, namely 2001:2, we calibrate the model for the periods pre and post the second quarter of 2001. We target a range of unconditional macro and asset-pricing moments based on consumption growth, inflation, dividend growth, stock returns, and bond returns. We assume that the quarterly frequency of the model coincides with the decision interval of the agent.[22]

We first describe how we calibrate the model and then we discuss the implied macro and asset-pricing moments. All calibrated parameters are reported in Table XII. The mean parameters for growth and inflation, $\mu_c(s_{t+1})$ and $\mu_\pi(s_{t+1})$, are set equal to their sample values for each sub-period. The mean of dividend growth, μ_d, is set equal to the full sample mean. The persistence of shocks to consumption growth, β_1, is set to 0.951 and 0.995 for the two periods. These values translate into 0.983 and 0.998 on a monthly frequency. The first value is in line with the existing long-run risk literature while the second value is higher since we find the persistence of consumption growth to be substantially higher in the second period compared to the first.

The β_2 parameter is set to -0.012 and 0.012 respectively, which means that inflation expectations have a negative impact on expected growth in the countercyclical state but a positive impact in the procyclical period. This creates a negative (positive) correlation between growth and inflation in the countercyclical (procyclical) period. The different signs of β_2 for the two states also allow the model to match the switching relation between price-dividend ratios and expected inflation, from negative to positive, that we documented earlier. More specifically, the sign of β_2 determines the sign of $A_{d,2}$ in Equation (13). The last of the β parameters is β_4 which governs the persistence of inflation. We find that the persistence of inflation was substantially higher during the countercyclical period than in the recent procyclical period. We therefore calibrate β_4 to 0.90 and 0.40 respectively.

The next set of parameters refers to the δ matrix which governs the size of long-run shocks to growth and inflation. The parameters governing shocks to expected growth, δ_1, are set to 0.12 and 0.15 for both periods respectively. The parameters δ_2 and δ_3 affect the correlation between growth and inflation and are set equal to -0.12 and 0.20 for δ_2 and to -0.10 and 0.9 for δ_3. This helps the model to match the switch from negative to positive macro correlations. Lastly, δ_4 governs the size of long-run shocks to inflation and is calibrated to 0.90 for both states.

Overall, the main difference in parameter values across regimes stems from matching the

[22]This means we abstract away from issues related to time-aggregation of consumption growth. See for example Bansal et al., (2007a), Bansal et al., (2007b), and Hasseltoft (2012), who all estimate long-run risk models using simulation estimators, taking into account time-aggregation of consumption growth.

significant shift in the growth-inflation correlation from negative to positive plus matching the large increase in growth persistence and the large drop in inflation persistence that occurred during the post-2000 period.

The persistence of volatility shocks v_π and their volatility σ_ν are calibrated to standard values in the long-run risk literature, 0.98 and $1 * 10^{-6}$ respectively. Dividend parameters and the preference parameters are also calibrated to standard values in the literature. The risk aversion is set to 10 and the EIS to 2. It is well-known that long-run risk models need an EIS above one in order to generate plausible asset pricing implications. The value of the EIS is subject to controversy. While for example Hall (1988), Campbell (1999), and Beeler and Campbell (2011) estimate the EIS to be close to zero, Attanasio and Weber (1993), Attanasio and Vissing-Jorgensen (2003), Chen et al. (2008), and Hasseltoft (2012) among others find the EIS to be above one. Lastly we need to calibrate the transition probabilities. We set them equal to the estimated values from the empirical regime-switching model, namely $p_{00} = 0.98$ and $p_{11} = 0.94$.

Having calibrated the model, we simulate the model 150000 quarters and evaluate the implied macro and asset-price moments. Table XIII reports the resulting macro moments. We report moments for the countercyclical period, the procyclical period, and for the full sample. The unconditional means of growth and inflation are matched perfectly by construction. Volatilities of the macroeconomic variables all lie close to their sample values. The table shows that the persistence of growth increased sharply post 2000 with a first-order autocorrelation coefficient of 0.77 versus 0.39 for the countercyclical period. The persistence of inflation also changed markedly but in the opposite direction with a large drop in the first-order autocorrelation coefficient from 0.84 in the countercyclical regime to 0.27 in the procyclical regime. Our calibration matches these sharp changes in persistence. We report the fourth-order autocorrelation coefficient for dividend growth since the moving-average procedure described above automatically induces positive autocorrelation for up to three lags.

Table XIV contains unconditional asset-price moments. The calibration generates model moments that are broadly in line with data. While the level of the equity risk premium and price-dividend ratios are broadly in line with data, the volatilities are lower than in data. The level of the nominal short rate is matched well and the model generates an upward sloping nominal yield curve in both regimes. However the model-implied slope of roughly 50 basis points is lower than observed in data. The model-implied real yield curve is downward sloping in the countercyclical period but upward sloping in the procyclical period. The fact that our regime-switching model can produce an upward sloping real term structure is interesting since standard long-run risk models can only produce downward sloping real term structures. We discuss this more in detail in Section 5.2.

Table XV reports various macro and asset correlations. First, the correlation between real growth and inflation changed from negative to positive in data, −0.42 versus 0.30. The model is able to match this shift. Second, the correlation between dividend yields and nominal yields changed sharply in data from 0.68 to −0.65. The model is able to generate a similar shift from positive to negative correlations, albeit the correlation in the procyclical period is more negative than in data. Third, the correlation between stock and bond returns changed substantially from positive to negative in data, 0.28 versus −0.63. The model matches this transition well.

Overall, we believe the model does a good job in matching key macro and asset-pricing moments. In particular, the model is able to match the large shifts in growth-inflation correlations and asset correlations. The model could of course do an even better job if we relaxed the many imposed restrictions. Our objective, however, has been to match the broad change in macro and asset-prices across the two regimes while keeping the model as parsimonious as possible.

5 Asset Pricing Implications

Given our calibrated parameters, we here discuss in detail the model-implications for bond risk premia, equity risk premia, slopes of the real and nominal term structures, and asset correlations.

5.1 Real and Nominal Bond Risk Premia

Let $h_{t+1,n}(s_{t+1}) = q_{t+1,n-1}(s_{t+1}) - q_{t,n}(s_t)$ denote the one period log holding period return on a real bond with a maturity of n periods. As we show in the Appendix, the bond risk premium can then be written as:

$$\begin{aligned} E[h_{t+1,n}(s_{t+1}) - r_{f,t}|I_t] &+ \frac{1}{2}\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Var[h_{t+1,n}(s_{t+1})|I_{t+1}] \\ &= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}}[A(s_{t+1}) + B(s_{t+1})\sigma^2_{\pi,t}], \\ B(s_{t+1}) &= [D_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_4(s_{t+1})]\lambda_{\varepsilon_\pi}(s_{t+1}). \end{aligned} \quad (19)$$

The same expression holds for nominal bond returns, $h^{\$}_{t+1,n}(s_{t+1})$, by replacing the A and B-coefficients by $A^{\$}$ and $B^{\$}$. The expressions for A, $A^{\$}$ and $B^{\$}$ are reported in the Appendix. Time-varying volatility of inflation $\sigma^2_{\pi,t}$ gives rise to time-varying bond risk premiums. The $B(s_{t+1})$ and $B(s^{\$}_{t+1})$ coefficients are determined by the market price of long-run inflation risk $\lambda_{\varepsilon_\pi}(s_{t+1})$ times the response of bond prices to inflation shocks. Positive inflation shocks raise nominal yields in both regimes while they lower (raise) real yields in the countercyclical (procyclical) regime. As discussed earlier, the market price of inflation risk is negative in the countercyclical regime and positive in the procyclical regime. This implies that nominal bond risk premia load positively on inflation volatility when inflation is countercyclical but negatively when inflation is procyclical. The model suggests the loading was positive for the pre-2000 period but negative post 2000. Real bond risk premia, however, load negatively on inflation volatility in both regimes since real bonds always provide a hedge against bad times.

Recall the empirical evidence reported earlier in Table V which showed how the relation between nominal yields and inflation uncertainty switches sign between the inflation regimes. The model can explain this effect by allowing for changes in the riskiness of nominal bonds. Note that the effect of inflation uncertainty on nominal yields is distinct from the level of inflation. An increase in the level of expected inflation represents a cash-flow effect on nominal bonds and is always bad for nominal bond returns and raises yields while an increase in inflation uncertainty can either increase or decrease nominal yields through a discount-rate channel.

Table XVI shows results from regressing the level of 5-year nominal rates onto expected inflation and inflation uncertainty inside the model. We simulate 150000 quarters and run regressions for the full simulated sample, for the countercyclical period of the sample, and for the procyclical period of the sample. First of all, simulated yields load positively on the level of expected inflation for all three samples which is expected. The slope coefficients for inflation uncertainty are more interesting. They suggest that model-implied rates load positively on inflation uncertainty for the full sample and for the countercyclical period. However, the coefficient on inflation uncertainty switches sign in the procyclical state: An increase in inflation uncertainty *lowers* nominal bond yields through its negative impact on bond risk premia.

5.2 Slope of the Real and Nominal Term Structure

A conventional way of expressing the slope of the term structure is to write it as the sum of expected future short rates plus a risk premium (term premium) part. In the case of a single regime, this can be written as:

$$y_{t,n} - y_{t,1} = \frac{1}{n} E(y_{t,1} + y_{t+1,1} + ... + y_{t+n-1,1}|I_t) - y_{t,1} + RPT_{t,n}. \tag{20}$$

Taking the unconditional expectation of this expression and using the law of iterated expectations yields that the first part equals zero. This implies that the average slope depends on the average risk premium:

$$E(y_{t,n} - y_{t,1}) = E(RPT_{t,n}), \tag{21}$$

which of course holds for both real and nominal bonds. Typically, long-run risk models generate negative risk premiums on real bonds which implies a downward sloping real yield curve. As mentioned earlier, this is in contrast to US data which indicates a positively sloped real yield curve using available data from 1997. The nominal yield curve, however, has been upward sloping on average in post-war data and for both regimes as was shown in Table XIV. To generate an upward-sloping nominal yield curve, consumption-based models typically rely on a negative unconditional covariance between growth and inflation observed in post-war data. A negative covariance implies that nominal bonds are risky which in turn implies a positive inflation risk premium and a positive slope. We find, however, that the covariance of growth and inflation turned positive around 2000. Does this necessarily imply a downward-sloping nominal yield curve in the model, in contrast to data? No.

In the case of multiple regimes, the average slope in a given regime also depends on expected future short rates. To see this, write the slope given today's regime s_t as:

$$y_{t,n}(s_t) - y_{t,1}(s_t) = \frac{1}{n}E[y_{t,1}(s_t) + y_{t+1,1}(s_{t+1}) + ... + y_{t+n-1,1}(s_{t+n-1})|I_t] - y_{t,1}(s_t) + RPT(s_t)_{t,n} \quad (22)$$

which holds for both real $(y_{t,n})$ and nominal yields $(y^{\$}_{t,n})$. For simplicity, consider a two-period bond where $n = 2$. The Appendix shows that the average yield-curve slope given regime $s_t = s$ can then be written as:

$$\begin{aligned} E[y_{t,2}(s_t) - y_{t,1}(s_t)|s_t = s] &= \frac{1}{2}\{p_{s,0}E[y_{t+1,1}|s_t = s, s_{t+1} = 0] + p_{s,1}E[y_{t+1,1}|s_t = s, s_{t+1} = 1]\} \\ &- \frac{1}{2}E[y_{t,1}(s_t)|s_t = s] \\ &+ E[RPT_{t,2}(s_t)|s_t = s]. \end{aligned} \quad (23)$$

The average slope for a given regime depends on both the risk premium part and on the expectations part.[23] Consider two regimes with low versus high short rates and suppose we stand in the low rate regime. Then the expectations part is positive as long as there is a non-zero probability of jumping to the high short rate state. And vice versa if we stand in the high short rate regime. Table XIV reported that the average nominal 3-month rate was 6.47 during the countercyclical pre-2000 period but only 1.78 in the procyclical post-2000 period. Consequently, our model implies that the average value of the expectations part in equation (22) is positive for the post-2000 period and negative for the pre-2000 period.

Using the analytical expressions provided in the Appendix, we decompose the slope of real and nominal term structures into the two components. Table XVII reports the decompositions. Starting with nominal bonds, the model implies a negative expectations part and a positive risk premium part for the countercyclical period. This is consistent with this regime being a high rate regime in which nominal bonds are risky assets. The net effect is a positive slope of 44 basis points. The procyclical period looks different. The average slope is still positive but now the expectations part is highly positive while the risk premium part is negative. This is consistent

[23]The Appendix contains derivations of the expectations part and the risk premium part in our model for any maturity n.

with the procyclical regime being a low-rate regime in which nominal bonds provide a hedge against bad times.

Turning to real bonds, Table XVII reports a negative slope in the countercyclical period of 46 basis points. Both components of the slope are negative as the pre-2000 period was characterized by high short rates and real bonds acting as hedges against bad times. Real bond risk premiums are also negative in the procyclical period but the expectations part is now positive since the regime is subject to low short rates. The net effect is a positive real slope. This effect is not present in standard long-run risk models since the slope in these models is exclusively determined by the risk premium part.

5.3 Equity Risk Premia

Let $r_{m,t+1}(s_{t+1})$ denote the one period log market return. The equity risk premium can then be written as:

$$
\begin{aligned}
E[r_{m,t+1}(s_{t+1}) - r_{f,t}|I_t] &+ \frac{1}{2}\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Var[r_{m,t+1}(s_{t+1})|I_{t+1}] \qquad (24)\\
&= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}}[A(s_{t+1}) + B(s_{t+1})\sigma^2_{\pi,t}],\\
B(s_{t+1}) &= [k_{d,1}A_{d,1}(s_{t+1})\delta_2(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_4(s_{t+1})]\lambda_{\varepsilon_\pi}(s_{t+1}).
\end{aligned}
$$

The $A(s_{t+1})$ coefficient and the derivation of expression (24) are reported in the Appendix for brevity. As with bonds, risk premiums on equity vary with inflation volatility. The $B(s_{t+1})$ coefficient is determined by the market price of long-run inflation risk $\lambda_{\varepsilon_\pi}(s_{t+1})$ times the impact of inflation shocks on real equity returns. In the countercyclical state, the market price of inflation risk is negative while inflation is bad for stock returns. Low returns in bad times implies that the equity risk premia moves positively with inflation uncertainty.

In the procyclical state, the market price of inflation risk is positive while stock returns are positively related to inflation. High stock returns in good times means that the equity risk premia moves positively with inflation uncertainty also in this regime. Using the price-dividend ratio as a proxy for expected excess stock returns, we find this to be consistent with data.

Table XVI shows results from regressing the log price-dividend ratio onto expected inflation and inflation uncertainty on simulated data inside the model. Results show that price-dividend ratios load negatively on both, expected inflation and inflation uncertainty for the full sample period. This is consistent with the voluminous literature that documents equity being a poor inflation hedge. Coefficients are similar for the countercyclical sample period. However, the coefficient on expected inflation switches sign in the procyclical state. The model suggests that equity prices respond differently to changes in the level of inflation as opposed to changes in inflation uncertainty. A procyclical inflation induces a positive relation between inflation levels and stock prices. This can interpreted as a cash-flow effect on stocks since higher growth in the model feeds into higher dividend growth. On the other hand, an increase in inflation uncertainty is always bad for stock prices since stock returns tend to always be procyclical. The model qualitatively matches the empirical regression results that were reported in Table III.

5.4 Asset Correlations

This section describes model implications for the correlation between stock and bond returns and for the correlation between dividend yields and nominal yields. Both of these correlations changed sign dramatically in the early 2000's as was shown in Figures 2 and 3. We show below that the model can account for this switch by accounting for the changing cyclicality of inflation.

5.4.1 Stock and Bond Returns

We show in the Appendix that the conditional covariance between stock and bond returns can be written as:

$$\begin{aligned} Cov[r^{\$}_{m,t+1}(s_{t+1}), h^{\$}_{t+1,n}(s_{t+1})|I_t] &= M_t + A + B\sigma^2_{\pi,t}, \\ B &= p_{s_t,0}[k_{d,1}A^0_{d,1}\delta^0_2 + k_{d,1}A^0_{d,2}\delta^0_4][D^{\$,0}_{1,n-1}\delta^0_2 + D^{\$,0}_{2,n-1}\delta^0_4] \\ &+ p_{s_t,1}[k_{d,1}A^1_{d,1}\delta^1_2 + k_{d,1}A^1_{d,2}\delta^1_4][D^{\$,1}_{1,n-1}\delta^1_2 + D^{\$,1}_{2,n-1}\delta^1_4], \end{aligned} \tag{25}$$

and where the M_t and A coefficients are reported in the Appendix. We choose to focus on the B coefficient since it is largest in magnitude and determines how the stock-bond covariance moves with inflation uncertainty. The B-coefficient is basically a probability weighted measure of the impact of inflation shocks on price-dividend ratios and nominal bonds in the two regimes. Based on the earlier discussion, we know that inflation shocks impact price-dividend ratios negatively in the countercyclical state and positively in the procyclical state. For nominal bonds we know that positive inflation shocks lower bond prices regardless of the economic state. It is then evident from Equation (25) that the conditional covariance moves positively with inflation uncertainty when inflation is bad for economic growth and negatively with inflation uncertainty when inflation is procyclical. One way to interpret this comovement is to think about how inflation uncertainty moves equity and bond risk premia. Higher inflation uncertainty always raises expected returns on equity but moves expected bond returns either up or down depending on the inflation regime.

We saw in Table VII that inflation uncertainty predicted quarterly stock-bond covariances positively during the countercyclical state but negatively during the procyclical period. We would like to simulate our model and run the same regressions inside the model. However, we cannot generate realized quarterly covariances in the model since the model is formulated on a quarterly frequency. Instead we report the value of the analytical B coefficient above. Table XVI reports that B is positive in the countercyclical state but switches to negative in the procyclical state. The model can match the switching behavior in data due to changes in the cyclical nature of inflation

Next we plot the model-implied conditional correlation between stock and bond returns. In order to do so we need empirical proxies for our state variables. We construct expected growth and inflation by projecting realized values onto a set of instruments and treat the fitted values as our state variables. Conditional variance of inflation is constructed by estimating an AR(1)-GARCH(1,1) on expected inflation.

Figure 10 plots the model-implied conditional correlations. Consistent with data, the model implies highly positive correlations throughout the 1970's and early 1980's but a sharp drop in correlations in the late 1980's which coincided with inflation briefly entering a procyclical period. As we approach the end of the 1990's correlations start to turn lower and drop sharply in the early 2000's as we enter the procyclical region. Model correlations then stay highly negative throughout the 2000's except for a sharp spike towards the end of the sample. Overall, the conditional correlations implied by the theoretical model share very similar dynamics to the rolling and estimated correlations based on data which are presented in Figures 1 and 9.

5.4.2 Dividend Yields and Nominal Yields

Since equity returns are closely related to changes in dividend yields and bond returns to changes in yields, the same mechanism can be used to explain why dividend yields and nominal yields comove. The existing literature focuses on the highly positive correlation between these two variables between 1960 and 2000. As mentioned earlier, this observation is often dubbed the Fed-model. However, it is rarely mentioned in the literature that this correlation changed dramatically during the last 10 years, from a correlation of 0.64 during 1965:1-2001:2 to a correlation of -0.57 during 2001:3-2011:4. The behavioral concept of inflation illusion has been extensively used in the literature to explain the positive comovement. However, the inflation illusion story cannot explain the significant shift to negative correlations. We find that our model can provide a rational explanation for why the comovement of dividend yields and nominal yields changes over time.

Consider the expression for the conditional covariance between dividend yields and nominal yields:

$$Cov[pd_{t+1}(s_{t+1}), y^{\$}_{t+1,n}(s_{t+1})|I_t] = M_t + A + B\sigma^2_{\pi,t}, \tag{26}$$

$$\begin{aligned} B &= -\frac{1}{n}\Big[p_{s_t,0}[A^0_{d,1}\delta^0_2 + A^0_{d,2}\delta^0_4][D^{\$,0}_{1,n-1}\delta^0_2 + D^{\$,0}_{2,n-1}\delta^0_4] \\ &+ p_{s_t,1}[A^1_{d,1}\delta^1_2 + A^1_{d,2}\delta^1_4][D^{\$,1}_{1,n-1}\delta^1_2 + D^{\$,1}_{2,n-1}\delta^1_4]\Big], \end{aligned}$$

and where M_t and A are reported in the Appendix. We focus on the B-coefficient since it is largest in magnitude and provides intuition of how the covariance moves with inflation uncertainty. Comparing the B-coefficient with the one in Equation (25), it is evident that they are very similar. The same argument as for the stock-bond covariance goes through for explaining the so called Fed-model. Changes in inflation uncertainty moves equity and bond risk premiums in the same direction when inflation is countercyclical. However inflation uncertainty moves stock and bond risk premia in opposite directions when inflation is procyclical since nominal bonds then provide insurance against bad times while equity is still risky. As a result, we find that movements in inflation risk together with changes in the cyclical nature of inflation can provide a plausible explanation for why dividend yields and nominal yields sometimes comove positively and sometimes diverge.

6 Understanding the Regimes

We have so far documented the existence of two distinct regimes in which macro and asset correlations are inversely related and have opposite signs. A natural question to ask is what characterizes these different regimes. One potential answer is that the two regimes differ in the magnitudes of output and inflation shocks. For example, negative output shocks should lower equity prices while the effect on nominal bonds depends on how output and inflation interact. If the negative output shock is associated with lower inflation (e.g., a negative aggregate demand shock), then nominal rates will decrease through both the real rate component of nominal interest rates (assuming procyclical real interest rates) and through lower inflation. Such a scenario produces poor stock returns but good bond returns, yielding a negative stock-bond correlation. Alternatively, a large positive shock to inflation that is detrimental to growth (e.g., an adverse supply shock) should raise nominal interest rates and lower equity prices. Such a shock would produce poor stock and bond returns, yielding a positive stock-bond correlation.

Another potential explanation is monetary policy and its impact on asset prices. For example, Kuttner (2001), Rigobon and Sack (2004), and Bernanke and Kuttner (2005) document that a lower (higher) Federal funds rate raises (lowers) equity and nominal bond prices.[24] This implies that changes in the Federal funds rate should produce positive stock-bond correlations. Furthermore, several papers have documented that the impact of monetary policy on the economy has changed over time. In particular, the impact of monetary policy on macroeconomic variables

[24]A potential explanation for these effects is the link between monetary policy and risk aversion as documented by Bekaert et al. (2012).

has decreased in more recent times.[25] It is therefore likely that the impact of monetary policy on stock-bond correlations also has varied over time.

With this as a background, we identify shocks to inflation, output, and monetary policy for the countercyclical period 1965:1-1999:4 and for the procyclical period 2000:1-2011:4 and study how they impact the stock-bond covariance. We do so by formulating a simple VAR consisting of inflation as measured by the GDP price deflator (π), real GDP growth ($\Delta(y)$), the Federal funds rate (ff), and the stock-bond covariance (cov).[26] The ordering is consequently $X_t = [\pi_t, \Delta(y)_t, ff_t, cov_t]$. All variables are observed quarterly. We consider a standard VAR(1) for the vector of observables $X_{t+1} = \mu + \beta X_t + \epsilon_{t+1}$, where $\epsilon_{t+1} \sim N(0, \Sigma)$. The VAR disturbances are assumed to be related to the underlying structural economic shocks, η, as follows: $\epsilon_{t+1} = A\eta_{t+1}$, where A is a lower triangular matrix and where $\eta_{t+1} \sim N(0, I)$.

In order to treat shocks to the Federal funds rate as structural monetary policy shocks, we need to impose some identification restrictions. We choose a simple recursive identification scheme where the matrix A is assumed to equal the Cholesky factor of Σ. The ordering of our variables implies that shocks to output and inflation affect the Federal funds rate contemporaneously while monetary policy shocks affect output and inflation with a one-period lag. These assumptions can of course be debated but have often been used in the literature on identifying monetary policy shocks.[27] The equation for the Federal funds rate can be viewed as a "Taylor rule" in which the Federal Reserve sets interest rates based on current inflation and output growth (Taylor, 1993). Our main interest, however, lies in the stock-bond covariance which is ordered last. Being ordered last implies that macro shocks and monetary policy shocks all have a contemporaneous effect on the stock-bond covariance.

We estimate the VAR with OLS, apply the Cholesky factorization, and then compute impulse response functions and variance decompositions. We estimate the VAR over two sub-periods, the countercyclical inflation period 1965:1-1999:4 and the procyclical inflation period 2000:1-2011:4.[28] Impulse response functions for the countercyclical period are displayed in Figure 11 and

[25]See for example Kuttner and Mosser (2002) and Boivin and Giannoni (2006).
[26]Inflation, GDP growth rate, and the Federal funds rate are obtained from the Federal Reserve Bank of St. Louis. The stock-bond covariance is computed as described earlier.
[27]See for example Christiano et al., (1998), Boivin and Giannoni (2006), and Olivei and Tenreyro (2007).
[28]Estimating the system as a regime-switching VAR yields impulse response functions that are qualitatively very

show the impact of a one-standard deviation shock to each variable. First, the figure shows that shocks to inflation were substantially more persistent than output shocks in the countercyclical period. Second, we find that inflation shocks had a negative impact on output, consistent with the negative correlation between growth and inflation that prevailed during the period. Furthermore, the results suggest that a one-standard deviation shock to the Federal funds rate causes a drop of around 0.15% in quarterly output growth, after which it recovers.[29] Our main interest, however, lies in the impact of shocks on the stock-bond covariance. The last graph indicates a large positive effect on the stock-bond covariance from a positive shock to the Federal funds rate. Hence, a contractionary monetary policy is associated with a positive comovement of stock and bond returns. This is in line with papers showing that a tightening in monetary conditions is typically bad for both stock and bond returns. The graph also shows a negative immediate impact on stock-bond covariances stemming from inflation shocks. Interestingly, the effect of monetary policy shocks on covariances is much stronger than the effects of output or inflation shocks.

Figure 12 shows impulse response functions for the procyclical period. The first observation is that output shocks were more persistent than inflation shocks, in contrast to the earlier period. Secondly, output shocks have a strong impact on all variables, and considerably stronger effects than during the first sample period. For example, a shock to output increases quarterly inflation by almost 0.10% after 2 quarters, producing a positive comovement between growth and inflation. Interestingly, the impact of monetary policy shocks on output and inflation are smaller compared to the first sample period. This is line with earlier studies cited above. The figure shows that stock-bond covariances were strongly impacted by output shocks during the post-2000 period. Even though inflation and monetary policy shocks still had sizeable effects on stock-bond covariances, their effect is dwarfed by output shocks. Overall, the impulse response functions suggest that shocks to inflation and monetary policy had a sizeable impact on stock-bond covariances during the countercyclical period while output shocks dominated during the procyclical period.

similar.

[29]The positive response of inflation to a positive shock to the Federal Funds rate is a version of the "price puzzle", documented by Sims (1992). It has been shown that this effect can be reduced by including commodity prices in the VAR. However, we refrain from doing so as we are mainly interested in stock-bond covariances.

Next, we consider variance decompositions of forecast errors. Table XVIII reports the fraction of variance accounted for by each shock. Our main interest lies at the stock-bond covariance. Considering first the countercyclical period, the table reports that shocks to inflation and monetary policy accounted for larger fractions compared to output shocks. Over a one-quarter horizon, inflation and monetary policy shocks accounted for 1% and 9% respectively while rising to 6% and 18% over a 20-quarter horizon. This can be compared with the 1% and 2% accounted for by output shocks. Turning to the procyclical period, the results differ strongly. Our results suggest that output shocks played an important role during the post-2000 period. In fact, we find that output shocks accounted for 25% of the variance in stock-bond covariance over one quarter and 56% over 20 quarters. In contrast, shocks to inflation and monetary policy played less of a role during this period.

Overall, our results suggest that inflation and monetary policy shocks had a sizeable impact on stock-bond covariances during the countercyclical period 1965:1-1999:4 while output shocks clearly dominated during the procyclical period 2000:1-2011:4. Hence, in order to understand why growth-inflation and stock-bond correlations change over time, our findings suggest that it depends on the relative magnitudes of nominal shocks versus real output shocks.

7 Conclusion

The correlation between returns on US stocks and Treasury bonds and the relation between inflation and asset prices have varied substantially over time. For example, the 1970-1980's were characterized by a highly positive correlation between stock and bond returns and a strong negative relation between inflation and price-dividend ratios. In contrast, the period 2000-2011 experienced the exact opposite with strongly negative asset correlations and a positive relation between inflation and equity valuations. We show that these observations line up remarkably well with the time-varying correlation between consumption growth and inflation going back to the 1930's. While the 1970-1980's was characterized by stagflation, we show that inflation switched to a procyclical state in the early 2000's.

We document in data that inflation risk is always negatively related to stock prices but can either decrease or increase bond prices depending on whether inflation is counter- or procyclical. In countercyclical inflation regimes, nominal bonds are risky assets and therefore perform badly as inflation risk increases. However, nominal bonds provide a hedge against bad times when inflation is procyclical. This produces a drop in nominal rates as inflation risk increases, generating positive bond returns. We find that this asymmetry in how inflation risk impacts asset prices helps explain why the stock-bond correlation switches sign over time.

We calibrate a long-run risk model that rationalizes our empirical findings and illustrates the connection between the cyclicality of inflation and the joint movements of bond and equity risk premia and inflation and asset prices. Persistent inflation shocks have real effects and affect both equity and bond risk premia. We introduce a Markov-switching regime mechanism into the model which allows the relation between real growth and inflation to switch sign. Equity and bond risk premia are both functions of inflation volatility in the model but the loading of bond risk premia on inflation uncertainty depends on the cyclicality of inflation and can therefore switch sign.

The model suggests that both equity and nominal bonds are risky assets when inflation is countercyclical, leading to a positive comovement of asset risk premia in response to changes in inflation uncertainty. In contrast, nominal bonds provide a hedge against inflation risk when inflation is procyclical while equity is still risky. This implies that a rise in inflation uncertainty drives equity and bond risk premia in different directions, causing their returns to correlate negatively. Hence, inflation uncertainty can produce both positive and negative stock-bond correlations depending on the inflation regime.

Results from a VAR analysis suggest that the positive stock-bond correlations during the countercyclical inflation period of 1965:1-1999:4 were dominated by nominal shocks in the form of inflation and monetary policy shocks. In contrast, we find that the period 2000:1-2011:4 with positive growth-inflation correlations and negative stock-bond correlations was dominated by real output shocks. Hence, in order to understand why growth-inflation and stock-bond correlations change over time, it seems important to consider the relative magnitudes of nominal shocks versus real shocks.

REFERENCES

Ang, Andrew, and Geert Bekaert, 2002a, International asset allocation with regime shifts, *Review of Financial Studies* 15, 1137–1187.

———, 2002b, Regime switches in interest rates, *Journal of Business and Economic Statistics* 20, 163–182.

———, 2002c, Short rate nonlinearities and regime switches, *Journal of Economic Dynamics and Control* 26, 1243–1274.

———, 2004, How do regimes affect asset allocation?, *Financial Analysts Journal* 60, 86–99.

Ang, Andrew, and Joseph Chen, 2002, Asymmetric correlations of equity portfolios, *Journal of Financial Economics* 2002, 443–494.

Ang Andrew, Geert Bekaert, and Min Wei, 2008, The term structure of real rates and expected inflation, *Journal of Finance* 63, 797–849.

Attanasio, Orazio P., and Annette Vissing-Jorgensen, 2003, Stock market participation, intertemporal substitution and risk aversion, *American Economic Review* 93, 383–391.

Attanasio, Orazio P., and Guglielmo Weber, 1993, Consumption growth, the interest rate and aggregation, *Review of Economic Studies* 60, 631–649.

Baele Lieven, Geert Bekaert, and Koen Inghelbrecht, 2010, The determinants of stock and bond return comovements, *Review of Financial Studies* 23, 2374–2428.

Bansal, Ravi, and Ivan Shaliastovich, 2010, A long-run risks explanation of predictability puzzles in bond and currency markets, Working Paper.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Bansal, Ravi, and Hao Zhou, 2002, Term structure of interest rates with regime shifts, *Journal of Finance* 57, 1997–2043.

Bansal Ravi, Dana Kiku, and Amir Yaron, 2007, Risks for the long run: Estimation and inference, Working Paper.

Bansal Ravi, George Tauchen, and Hao Zhou, 2004, Regime shifts, risk premiums in the term structure, and the business cycle, *Journal of Business and Economic Statistics* 22, 396–409.

Bansal Ravi, Robert F. Dittmar, and Christian T. Lundblad, 2005, Consumption, dividends, and the cross section of equity returns, *Journal of Finance* 60, 1639–1672.

Bansal Ravi, Ronald Gallant, and George Tauchen, 2007, Rational pessimism, rational exuberance, and asset pricing models, *Review of Economic Studies* 74, 1005–1033.

Beeler, Jason, and John Y. Campbell, 2011, The long-run risk model and aggregate asset prices: An empirical assessment, Working Paper.

Bekaert, Geert, and Eric Engstrom, 2010, Inflation and the stock market: Understanding the fed-model, *Journal of Monetary Economics* 57, 278–294.

Bekaert, Geert, and Xiaozheng Wang, 2010, Inflation risk and the inflation risk premium, *Economic Policy* 25, 755–806.

Bekaert Geert, Eric Engstrom, and Steven R. Grenadier, 2010, Stock and bond returns with moody investors, *Journal of Empirical Finance* 17, 867–894.

Bekaert Geert, Marie Hoerova, and Marco Lo Duca, 2012, Risk, uncertainty, and monetary policy, Working Paper.

Bernanke, Ben S., and Kenneth N. Kuttner, 2004, What explains the stock market's reaction to federal reserve policy?, *Journal of Finance* 60, 1221–1258.

Bikbov, Ruslan, and Mikhail Chernov, 2008, Monetary policy regimes and the term structure of interest rates, Working Paper.

Boivin, Jean, and Marc P. Giannoni, 2006, Has monetary policy become more effective?, *Review of Economic Studies* 88, 445–462.

Bollerslev, Tim, 1986, Generalized autoregressive conditional heteroscedasticity, *Journal of Econometrics* 31, 307–327.

Boudoukh, Jacob, 1993, An equilibrium model of nominal bond prices with inflation-output correlation and stochastic volatility, *Journal of Money, Credit and Banking* 25, 636–665.

Boyer H. Brian, Michael S. Gibson, and Mico Loretan, 1999, Pitfalls in tests for changes in correlations, Board of Governors of the Federal Reserve System, International Finance Discussion Papers No 597.

Campbell, John Y., 1993, Intertemporal asset pricing without consumption data, *American Economic Review* 83, 487–512.

——— , 1996, Understanding risk and return, *Journal of Political Economy* 104, 298–345.

——— , 1999, Asset prices, consumption and the business cycle, in John B. Taylor, and Michael Woodford, ed.: *Handbook of Macroeconomics* (Elsevier Science, North-Holland: Amsterdam).

——— , and John Ammer, 1993, What moves the stock and bond markets? a variance decomposition for long-term asset returns, *Journal of Finance* 48, 3–37.

Campbell, John Y., and Robert J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–227.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Inflation illusion and stock prices, *American Economic Review* 94, 19–23.

Campbell John Y., Adi Sunderam, and Luis M. Viceira, 2010, Inflation bets or deflation hedges? the changing risks of nominal bonds, Working Paper.

Cecchetti Stephen G., Pok-Sang Lam, and Nelson C. Mark, 1990, Mean reversion in equilibrium asset prices, *American Economic Review* 80, 398–418.

Chen Xiaohong, Jack Favilukis, and Sydney C. Ludvigson, 2008, An estimation of economic models with recursive preferences, Working Paper.

Chesnay, Francois, and Eric Jondeau, 2001, Does correlation between stock returns really increase during turbulent periods?, Economic Notes.

Christiano Lawrence, Martin Eichenbaum, and Charles L. Evans, 1998, Monetary policy shocks: What have we learned and to what end?, NBER Working Paper 6400.

Cohen Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2005, Money illusion in the stock market: The modigliani-cohn hypothesis, *Quarterly Journal of Economics* 120, 639–668.

Connolly Robert, Chris Stivers, and Licheng Sun, 2005, Stock market uncertainty and the stock-bond return relation, *Journal of Financial and Quantitative Analysis* 40, 161–194.

Constantinides, George M., and Anisha Ghosh, 2011, The predictability of returns with regime-shifts in consumption and dividend growth, Working Paper.

Dai Qiang, Kenneth J. Singleton, and Wei Yang, 2007, Regime shifts in a dynamic term structure model of u.s. treasury bond yields, *Review of Financial Studies* 20, 1669–1706.

David, Alexander, and Pietro Veronesi, 2009, Inflation and earnings uncertainty and volatility forecasts: A structural form approach, Working Paper.

Duffie Darrell, Mark Schroder, and Costis Skiadas, 1997, A term structure model with preferences for the timing of resolution of uncertainty, *Economic Theory* 9, 3–22.

Engle, Robert F., 1982, Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation, *Econometrica* 50, 987–1007.

Epstein, Larry G., and Stanley E. Zin, 1989, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–968.

Eraker, Bjorn, 2008, Affine general equilibrium models, *Management Science* 54, 2068–2080.

Eraker Bjorn, Ivan Shaliastovich, and Wenyu Wang, 2011, Durable goods, inflation risk, and the equilibrium term structure, Working Paper.

Evans, Martin D., 1998, Real risk, inflation risk, and the term structure, *Economic Journal* 113, 345–389.

Fama, Eugene F., 1981, Stock returns, real activity, inflation, and money, *American Economic Review* 71, 545–565.

——— , and Michael R. Gibbons, 1982, Inflation, real returns and capital investment, *Journal of Monetary Economics* 9, 297–323.

Geske, Robert, and Richard Roll, 1983, The fiscal and monetary linkages between stock returns and inflation, *Journal of Finance* 38, 1–33.

Gray, Stephen F., 1996, Modeling the conditional distribution of interest rates as a regime-switching process, *Journal of Financial Economics* 42, 27–62.

Hall, Robert E., 1988, Intertemporal substitution in consumption, *Journal of Political Economy* 96, 339–357.

Hamilton, James D., 1988, Rational-expectations econometric analysis of changes in regime: An investigation of the term structure of interest rates, *Journal of Economic Dynamics and Control* 12, 385–423.

———, 1989, A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica* 57, 357–384.

———, 1994, *Time series analysis*, Princeton University Press, Princeton.

Hasseltoft, Henrik, 2009, The fed-model and the changing correlation between stock and bond returns: An equilibrium approach, Working Paper.

———, 2012, Stocks, bonds, and long-run consumption risks, *Journal of Financial and Quantitative Analysis* 47, 309–332.

Jennrich, Robert I., 1970, An asymptotic chi-square test for the equality of two correlation matrices, *Journal of the American Statistical Association* 65, 904–912.

Kaul, Gautam, 1987, Stock returns and inflation, *Journal of Financial Economics* 18, 253–276.

Kuttner, Kenneth N., 2001, Monetary policy surprises and interest rates: Evidence from the fed funds futures market, *Journal of Monetary Economics* 47, 523–544.

———, and Patricia C. Mosser, 2002, The monetary transmission mechanism: Some answers and further questions, Federal Reserve Bank New York Economic Policy Review.

Lettau Martin, Sydney Ludvigson, and Jessica Wachter, 2008, The declining equity premium: What role does macroeconomic risk play?, *Review of Financial Studies* 21, 1653–1687.

Marshall, David A., 1992, Inflation and asset returns in a monetary economy, *Journal of Finance* 47, 1315–1342.

Modigliani, Franco, and Richard A. Cohn, 1979, Inflation, rational valuation and the market, *Financial Analysts Journal* 35, 24–44.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Olivei, Giovanni, and Silvana Tenreyro, 2007, The timing of monetary policy shocks, *American Economic Review* 97, 636–663.

Pennacchi, George G., 1991, Identifying the dynamics of real interest rates and inflation: Evidence using survey data, *Review of Financial Studies* 4, 53–86.

Piazzesi, Monika, and Martin Schneider, 2006, Equilibrium yield curves, in Michael Woodford Daron Acemoglu, and Kenneth Rogoff, ed.: *NBER Macroeconomics Annual: 2006* (MIT Press: Cambridge).

Restoy, Fernando, and Philippe Weil, 1998, Approximate equilibrium asset prices, NBER Working Paper 6611.

Rigobon, Roberto, and Brian Sack, 2004, The impact of monetary policy on asset prices, *Journal of Monetary Economics* 51, 1553–1575.

Ritter, Jay R., and Richard S. Warr, 2002, The decline of inflation and the bull market of 1982-1999, *Journal of Financial and Quantitative Analysis* 37, 29–61.

Shiller, Robert J., and Andrea E. Beltratti, 1992, Stock prices and bond yields. can their comovements be explained in terms of present value models?, *Journal of Monetary Economics* 30, 25–46.

Sims, Christopher A., 1992, Interpreting the macroeconomic time series facts, *European Economic Review* 36, 975–1011.

Stulz, Rene E., 1986, Asset pricing and expected inflation, *Journal of Finance* 41, 209–223.

Taylor, John B., 1993, Discretion versus policy rules in practice, *Carnegie-Rochester Conference Series on Public Policy* 39, 195–214.

Viceira, Luis M., 2010, Bond risk, bond return volatility, and the term structure of interest rates, forthcoming *International Journal of Forecasting.*

Weil, Philippe, 1989, The equity premium puzzle and the risk-free rate puzzle, *Journal of Monetary Economics* 24, 401–421.

8 Tables

Table I. Unconditional Correlation Matrices and Variances over Subperiods This table presents unconditional correlation matrices and variances based on quarterly data over the full sample period 1965-2011 and the considered subperiods 1965-2000 (countercyclical period) and 2001-2011 (procyclical period). Stock and bond returns are excess returns.

	Correlation Matrix				Variance
	Cg	Inf	Stock	Bond	
1965-2011					
Cg	1.000	–0.161	0.191	-0.128	0.227
Inf		1.000	–0.086	–0.241	0.415
Stock			1.000	0.073	72.54
Bond				1.000	12.12
1965-2000					
Cg	1.000	–0.420	0.154	–0.083	0.212
Inf		1.000	–0.201	–0.202	0.412
Stock			1.000	0.283	66.70
Bond				1.000	12.77
2001-2011					
Cg	1.000	0.298	0.349	–0.177	0.144
Inf		1.000	0.273	–0.329	0.263
Stock			1.000	–0.631	94.70
Bond				1.000	9.583

Table II. Jennrich (1970) Test of Equality of Correlation Matrices over Subperiods This table presents results from a Jennrich (1970) test for constant unconditional correlations. The test statistic is asymptotically distributed as a Chi-square with the degree of freedom equal to the number of correlation coefficients.

Model	Degree of freedom	1965-2000 compared to 2001-2011	
		Statistics	p-value
Cg-Inf-Stock-Bond	6	50.344	0.000
Cg-Inf	1	19.368	0.000
Stock-Bond	1	27.577	0.000
Stock-Inflation	1	7.446	0.006

Table III. Regressing Price-Dividend Ratios onto Inflation and Inflation Risk This table presents results from regressing log price-dividend ratios onto expected inflation (β_π) and inflation risk ($\beta_{\sigma_\pi^2}$): $pd_t = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma_\pi^2}\sigma_{\pi,t}^2 + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma_\pi^2}$	t-stat	R^2
Full sample	–0.16	–2.22	–47.76	–5.10	0.48
Countercyclical state	–0.20	–3.34	–30.20	–3.86	0.44
Procyclical state	0.10	1.09	–84.58	–6.35	0.51

Table IV. Regressing Price-Dividend Ratios onto Inflation, Inflation Risk, Consumption Growth and Consumption Risk This table presents results from regressing log price-dividend ratios onto expected inflation (β_π), inflation risk ($\beta_{\sigma^2_\pi}$), consumption growth (β_{cg}) and consumption risk ($\beta_{\sigma^2_{cg}}$): $pd_t = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi}\sigma^2_{\pi,t} + \beta_{cg}x_{cg,t} + \beta_{\sigma^2_{cg}}\sigma^2_{cg,t} + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data								
	β_π	t-stat	$\beta_{\sigma^2_\pi}$	t-stat	β_{cg}	t-stat	$\beta_{\sigma^2_{cg}}$	t-stat	R^2
Full sample	–0.15	–1.79	–47.86	–5.33	–0.19	–1.52	–1.22	0.67	0.49
Countercyclical state	–0.22	–3.48	–29.30	–3.78	–0.16	–1.47	–1.27	0.94	0.45
Procyclical state	0.09	2.61	–72.58	–3.77	0.48	6.00	23.12	2.68	0.74

Table V. Regressing Nominal Yields onto Inflation and Inflation Risk This table presents results from regressing 5-year nominal interest rates onto expected inflation (β_π) and inflation risk ($\beta_{\sigma^2_\pi}$): $y^{\$}_{t,5y} = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi}\sigma^2_{\pi,t} + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma^2_\pi}$	t-stat	R^2
Full sample	1.61	2.86	244.68	3.19	0.34
Countercyclical state	0.42	0.78	223.89	3.04	0.25
Procyclical state	0.50	1.40	–382.72	–2.49	0.27

Table VI. Regressing Nominal Yields onto Inflation, Inflation Risk, Consumption Growth and Consumption Risk This table presents results from regressing 5-year nominal interest rates onto expected inflation (β_π), inflation risk ($\beta_{\sigma^2_\pi}$), consumption growth (β_{cg}) and consumption risk ($\beta_{\sigma^2_{cg}}$): $y^{\$}_{t,5y} = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi}\sigma^2_{\pi,t} + \beta_{cg}x_{cg,t} + \beta_{\sigma^2_{cg}}\sigma^2_{cg,t} + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data								
	β_π	t-stat	$\beta_{\sigma^2_\pi}$	t-stat	β_{cg}	t-stat	$\beta_{\sigma^2_{cg}}$	t-stat	R^2
Full sample	1.45	3.55	251.14	3.07	3.64	3.56	21.17	1.61	0.45
Countercyclical state	0.46	0.83	199.99	2.47	1.09	0.99	15.60	1.15	0.26
Procyclical state	0.58	2.21	–416.12	–2.52	0.73	0.89	104.64	1.42	0.29

Table VII. Predicting Covariance of Stock and Bond Returns This table presents results from predicting quarterly covariances between returns on US stocks and Treasury bonds using inflation risk: $\sigma(r_{stock,t+1}, r_{bond,t+1}) = \alpha + \beta_{\sigma^2_\pi}\sigma^2_{\pi,t} + \epsilon_t$. Dependent variable is the realized quarterly covariance between stock and bond returns computed using daily returns. Independent variable is the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data		
	$\beta_{\sigma^2_\pi}$	t-stat	R^2
Full sample	11.33	4.02	0.08
Countercyclical state	5.16	2.30	0.08
Procyclical state	–40.64	–2.33	0.06

Table VIII. Estimation Results for Markov-Switching Model This table presents results from estimating a two-regime MS-VAR model using maximum likelihood. Sample period is 1965:1 to 2011:4 and the model is formulated as indicated in Equation (1). Stock and bond returns are excess returns. Standard errors in parentheses are computed using the Hessian. Tomorrow's state s_{t+1} is presumed to follow a two-state Markov chain with transition probabilities $p_{ij} = P(s_{t+1} = j|s_t = i)$ where $\sum_{j=1}^{N} p_{ij} = 1$ and $0 < p_{ij} < 1$. The probability of ending up in tomorrow's state $s_{t+1} = (0,1)$ given today's state $s_t = (0,1)$ is governed by the transition probability matrix P:

$$P = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix}.$$

	Countercyclical State				Procyclical State			
	Cg	Inf	Stock	Bond	Cg	Inf	Stock	Bond
β Matrix								
Cg	0.347	–0.122	0.012	0.015	0.675	0.033	0.006	0.006
	(0.084)	(0.062)	(0.005)	(0.011)	(0.087)	(0.067)	(0.004)	(0.011)
Inf	0.138	0.866	–0.004	–0.008	0.667	–0.164	0.007	–0.047
	(0.067)	(0.050)	(0.004)	(0.009)	(0.170)	(0.127)	(0.007)	(0.020)
Stock	–1.274	–1.251	0.001	0.315	4.812	–2.826	0.150	0.388
	(1.627)	(1.221)	(0.051)	(0.197)	(3.983)	(2.812)	(0.205)	(0.6163)
Bond	–0.426	–1.167	–0.060	–0.047	–2.605	2.181	–0.070	–0.068
	(0.714)	(0.532)	(0.038)	(0.089)	(1.228)	(0.950)	(0.056)	(0.177)
Ω Matrix								
Cg	0.174	–0.040	0.671	–0.182	0.036	0.007	0.277	0.013
	(0.021)	(0.012)	(0.277)	(0.124)	(0.009)	(0.011)	(0.291)	(0.067)
Inf		0.110	–0.614	–0.202		0.122	1.127	–0.257
		(0.013)	(0.218)	(0.098)		(0.026)	(0.556)	(0.155)
Stock			59.012	8.865			99.156	–16.286
			(7.106)	(2.417)			(21.473)	(4.940)
Bond				12.248				7.762
				(1.466)				(1.658)
μ Vector								
μ	0.638	0.060	3.268	2.101	0.139	0.468	–0.042	0.722
	(0.123)	(0.099)	(2.468)	(1.056)	(0.057)	(0.104)	(0.162)	(0.697)
Probs								
p_{11}	0.977							
	(0.014)							
p_{22}	0.939							
	(0.039)							
fval	1259.7							

Table IX. Unconditional Correlations implied by Estimated Markov-Switching Model This table presents the unconditional correlation matrix implied by the estimated empirical Markov-Switching model.

	Countercyclical State				Procyclical State			
	Cg	Inf	Stock	Bond	Cg	Inf	Stock	Bond
Unconditional Correlations								
Cg	1	–0.42	0.20	–0.11	1	0.41	0.18	–0.11
Inf		1	–0.23	–0.20		1	0.30	–0.32
Stock			1	0.32			1	–0.60
Bond				1				1

Table X. Jennrich (1970) Test of Equality of Unconditional Correlation Matrices implied by Estimated Markov-Switching Model over Regimes This table presents a formal test for constant unconditional correlation implied by the Markov-Switching model across regimes: The Jennrich (1979) test of equality of two correlation matrices computed over independent subsamples. The Jennrich test statistic is asymptotically distrbuted as a Chi-square with the degree of freedom equal to the number of correlation coefficients.

Model	Degree of freedom	1965-2000 compared to 2001-2011	
		Statistics	p-value
Cg-Inf-Stock-Bond	6	58.993	0.000
Cg-Inf	1	24.755	0.000
Stock-Bond	1	28.671	0.000
Stock-Inflation	1	9.350	0.002

Table XI. LR test statistic for regime-independent (conditional) correlations This table presents a likelihood ratio (LR) test for the null hypothesis of a constant conditional correlation matrix across regimes. The LR test statistic is 2(ln L(θ) - ln L(θ_0)), with θ_0 corresponding to the parameter vector resulting under the null hypothesis. Under the null, the test statistic is distributed χ^2 with $n(n-1)/2$ degrees of freedom.

Model	Degree of freedom	LR test statistic H_0: $\rho(S_t) = \rho$	
		Statistics	p-value
Cg-Inf-Stock-Bond	6	25.387	0.0003

Table XII. Calibrated Model Parameters This table presents calibrated parameters for the two economic states. Parameters are calibrated as to match both standard macro and asset pricing moments as well as the various relations between stocks and bonds and between inflation and asset prices. The transition probabilities are the ones we estimated in the empirical regime-switching model. The countercyclical state refers to 1965:1-2001:2 and the procyclical state to 2001:3-2011:4.

	Countercyclical state	Procyclical state
μ_c	0.0081	0.0039
μ_π	0.0114	0.0067
μ_d	0.0035	0.0035
β_1	0.951	0.995
β_2	–0.012	0.012
β_4	0.90	0.40
δ_1	0.12	0.15
δ_2	–0.12	0.2
δ_3	–0.1	0.9
δ_4	0.9	0.9
σ_π	0.00375	0.00375
v_π	0.98	0.98
$\sigma_\nu * 10^{-6}$	1	1
σ_c	0.0031	0.0031
ϕ	2	2
φ	5	5
γ	10	10
ψ	2	2
δ	0.998	0.998
p_{00}	0.98	
p_{11}	0.94	

Table XIII. Macro Moments This table presents unconditional quarterly moments of the macro variables. Sample statistics refer to the countercyclical period 1965:1-2001:2, to the procyclical period 2001:3-2011:4, and to the full sample period 1965:1-2011:4. Model statistics are based on a simulation of 150000 quarters. AC(k) denotes the autocorrelation for k lags. Standard errors for the observed data, denoted SE, are computed as in Newey and West (1987), using four lags.

	Countercyclical State			Procyclical State			Full Sample		
	Model	Data	SE	Model	Data	SE	Model	Data	SE
Consumption growth, Δc									
Mean	0.81	0.81	(0.06)	0.38	0.39	(0.11)	0.70	0.71	(0.06)
Std.Dev.	0.43	0.46	(0.04)	0.54	0.38	(0.09)	0.50	0.48	(0.04)
AC(1)	0.48	0.39	(0.05)	0.65	0.77	(0.12)	0.59	0.52	(0.08)
Inflation, π									
Mean	1.14	1.14	(0.11)	0.67	0.67	(0.08)	1.03	1.04	(0.09)
Std.Dev.	0.76	0.64	(0.08)	0.51	0.51	(0.13)	0.73	0.65	(0.08)
AC(1)	0.90	0.84	(0.05)	0.42	0.27	(0.14)	0.85	0.77	(0.07)
Dividend growth, Δd									
Mean	0.35	0.22	(0.18)	0.32	0.82	(0.75)	0.34	0.35	(0.22)
Std.Dev.	1.66	1.46	(0.15)	1.78	2.82	(0.66)	1.69	1.86	(0.24)
AC(4)	0.12	-0.02	(0.13)	0.23	0.06	(0.17)	0.15	0.07	(0.12)

Table XIV. Asset Price Moments This table presents unconditional asset-price moments. All results are reported on an annualized basis. Sample statistics refer to the countercyclical period 1965:1-2001:2, to the procyclical period 2001:3-2011:4 and to the full sample period 1965:1-2011:4. Model statistics are based on a simulation of 150000 quarters. Standard errors for the observed data, denoted SE, are computed as in Newey and West (1987), using four lags.

	Countercyclical State			Procyclical State			Full Sample		
	Model	Data	SE	Model	Data	SE	Model	Data	SE
Equity									
$E(r_m - r_f)$	0.79	1.05	(0.62)	0.74	0.45	(1.54)	0.78	0.91	(0.60)
$\sigma(r_m - r_f)$	3.50	8.12	(0.75)	4.93	9.73	(1.40)	3.88	8.52	(0.67)
$E(pd)$	3.44	3.44	(0.06)	3.38	3.83	(0.05)	3.43	3.52	(0.06)
$\sigma(pd)$	0.12	0.34	(0.04)	0.21	0.19	(0.04)	0.15	0.35	(0.03)
Nominal Bonds									
$E(y_{3m}^{\$})$	6.36	6.47	(0.44)	3.12	1.78	(0.54)	5.59	5.43	(0.48)
$E(y_{5y}^{\$} - y_{3m}^{\$})$	0.44	0.98	(0.18)	0.47	1.40	(0.27)	0.44	1.07	(0.15)
$\sigma(y_{3m}^{\$})$	2.74	2.57	(0.40)	2.35	1.68	(0.27)	2.99	3.09	(0.38)
$\sigma(y_{5y}^{\$} - y_{3m}^{\$})$	1.81	1.16	(0.12)	1.74	0.94	(0.13)	1.79	1.13	(0.10)
Real Bonds									
$E(y_{3m})$	1.83			0.34			1.48		
$E(y_{5y})$	1.37			0.40			1.14		
$\sigma(y_{3m})$	0.62			0.93			0.94		
$\sigma(y_{5y})$	0.48			0.81			0.71		

Table XV. Macro and Asset Correlations This table presents unconditional correlations of macro and asset-price data. $Corr(\Delta c, \pi)$ refers to the correlation between consumption growth and inflation, $Corr(dp, y^{\$}_{5y})$ refers to the correlation between dividend yields and nominal yields, $Corr(r_{stock}, r_{bond})$ refers to the correlation between excess stock and bond returns, $Corr(\Delta c, \Delta d)$ is the correlation between consumption growth and dividend growth and $Corr(\Delta d, \pi)$ refers to the correlation between dividend growth and inflation. Model statistics are based on a simulation of 150000 quarters. The countercyclical state refers to 1965:1-2001:2 and the procyclical state to 2001:3-2011:4. Standard errors for the observed data, denoted SE, are computed as in Newey and West (1987), using four lags.

	Countercyclical State			Procyclical State			Full Sample		
	Model	Data	SE	Model	Data	SE	Model	Data	SE
$Corr(\Delta c, \pi)$	-0.41	-0.42	(0.10)	0.18	0.30	(0.19)	-0.15	-0.16	(0.15)
$Corr(dp, y^{\$}_{5y})$	0.46	0.68	(0.05)	-0.97	-0.65	(0.06)	-0.13	0.70	(0.06)
$Corr(r_{stock}, r_{bond})$	0.37	0.28	(0.08)	-0.59	-0.63	(0.08)	0.01	0.07	(0.11)
$Corr(\Delta c, \Delta d)$	0.26	0.19	(0.07)	0.40	0.49	(0.07)	0.28	0.19	(0.09)
$Corr(\Delta d, \pi)$	-0.20	-0.13	(0.08)	0.11	0.06	(0.06)	-0.14	-0.10	(0.08)

Table XVI. Inflation and Asset Prices - Model Regressions This table presents results from running regressions using simulated asset prices and inflation inside the model. The first regression regresses log price-dividend ratios onto expected inflation and the conditional inflation variance, i.e. the two state variables: $pd_t = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi} \sigma^2_{\pi,t} + \epsilon_t$. The second regression regresses the nominal 5-year interest rate onto expected inflation and the conditional inflation variance: $y^{\$}_{t,5y} = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi} \sigma^2_{\pi,t} + \epsilon_t$. Finally, we report the analytical coefficient governing the relation between the conditional stock-bond covariance and the conditional inflation variance from Equation (25). We report the analytical coefficient since the model does not allow for simulation of realized covariances based on daily returns, as in data. Model statistics are based on a simulation of 150000 quarters.

	Price-Dividend Ratios			Nominal Interest Rates			Stock-Bond Cov
	β_π	$\beta_{\sigma^2_\pi}$	R^2	β_π	$\beta_{\sigma^2_\pi}$	R^2	$\beta_{\sigma^2_\pi}$
Full Sample	–0.08	–1.02	0.25	1.17	0.73	0.24	
Countercyclical state	–0.10	–1.01	0.60	1.19	2.89	0.89	36.16
Procyclical state	0.12	–1.03	0.13	0.91	–5.43	0.32	–32.15

Table XVII. Yield Curve Slope Components This table presents the different components of the slopes of real and nominal yield curves within our model. All results are reported on an annualized basis. Model statistics are based on a simulation of 150000 quarters.

	Countercyclical State			Procyclical State			Full Sample		
	Slope	EH-part	RP-part	Slope	EH-part	RP-part	Slope	EH-part	RP-part
<u>Nominal Bonds</u>									
$E(y^{\$}_{5y} - y^{\$}_{3m})$	0.44	–0.38	0.82	0.47	1.20	–0.74	0.44	0.00	0.44
<u>Real Bonds</u>									
$E(y_{5y} - y_{3m})$	–0.46	–0.17	–0.29	0.06	0.55	–0.49	–0.34	0.00	–0.34

Table XVIII. Variance decompositions This table presents variance decompositions of forecast errors stemming from one standard deviation shocks to inflation, real output growth, Federal funds rate, and stock-bond covariance. The shocks are retrieved from a VAR(1) with the ordering $X_t = [inflation, output, Fed\,funds\,rate, covariance]$ and where an orthogononalization is done using the Cholesky factor.

	Variable	Horizon (quarters)	Inflation shock	Output Shock	Fed shock	Cov shock
Countercyclical period 1965:1-1999:4	Inflation	1	1.00	0.00	0.00	0.00
		20	0.96	0.01	0.01	0.02
	Output	1	0.01	0.99	0.00	0.00
		20	0.08	0.82	0.11	0.01
	Fed rate	1	0.03	0.96	0.01	0.00
		20	0.35	0.09	0.55	0.01
	Stock-Bond cov	1	0.01	0.01	0.09	0.89
		20	0.06	0.02	0.18	0.74
Procyclical period 2000:1-2011:4	Inflation	1	1.00	0.00	0.00	0.00
		20	0.73	0.23	0.01	0.03
	Output	1	0.00	1.00	0.00	0.00
		20	0.01	0.93	0.02	0.04
	Fed rate	1	0.01	0.03	0.96	0.00
		20	0.06	0.59	0.31	0.04
	Stock-Bond cov	1	0.02	0.25	0.07	0.66
		20	0.01	0.56	0.04	0.39

9 Figures

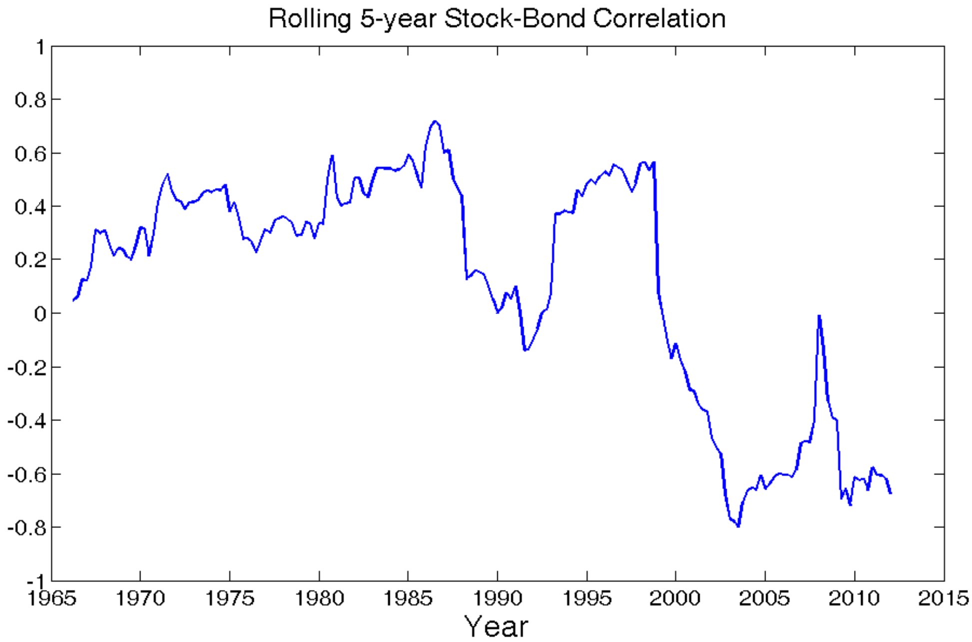
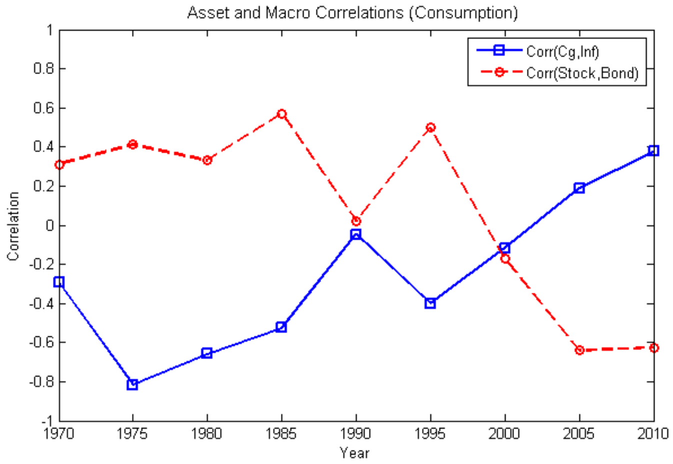
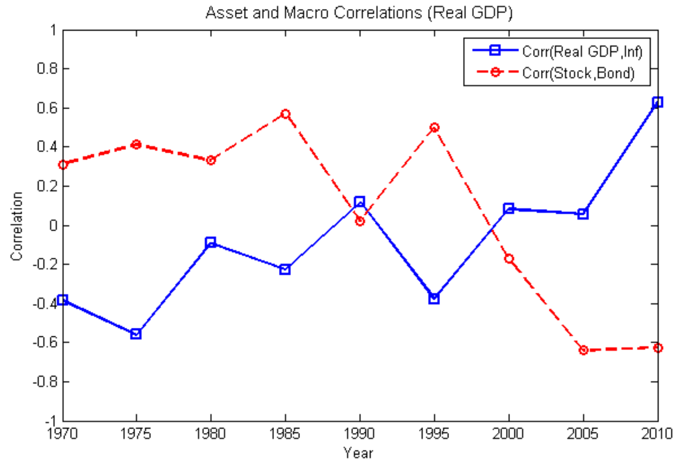


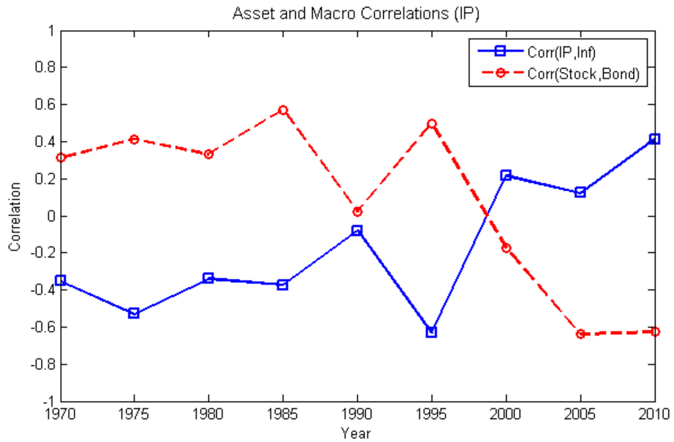
Figure 1. Rolling 5-year correlations between quarterly excess returns on US stocks and nominal 5-year Treasury bonds for the period March 1961 to December 2011.



(a) Correlation between quarterly real consumption growth and inflation and between returns on US stocks and Treasury bonds.



(b) Correlation between quarterly real GDP growth and inflation and between returns on US stocks and Treasury bonds.



(c) Correlation between quarterly US industrial production growth and inflation and between returns on US stocks and Treasury bonds.

Figure 2. Asset and Macro Correlations computed for non-overlapping 5-year intervals over the period 1965:1-2011:4.

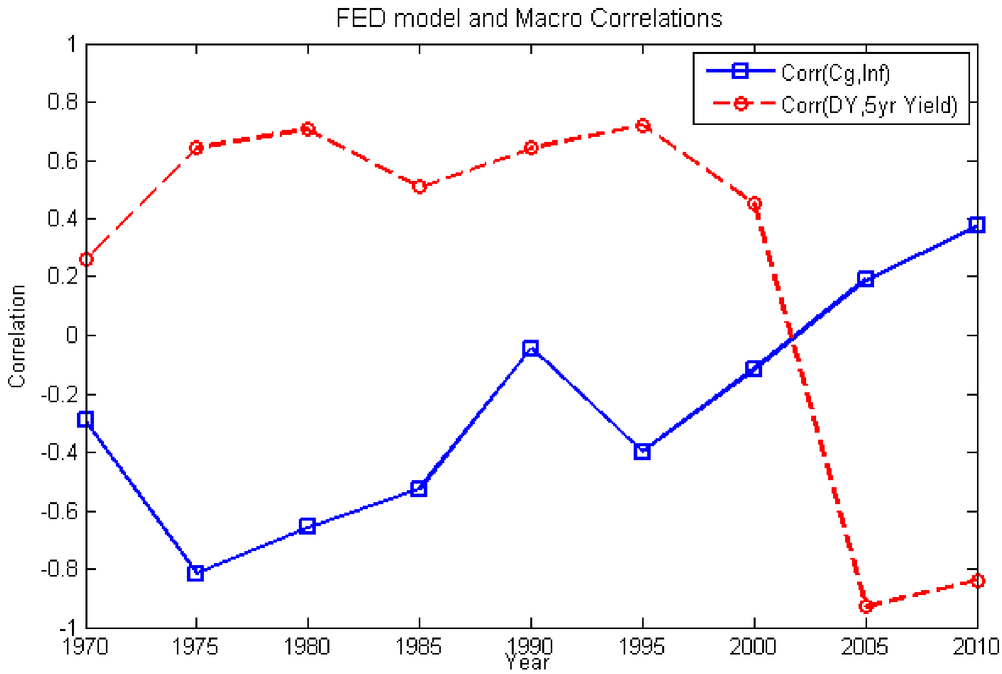


Figure 3. Correlation between quarterly real consumption growth and inflation and between the dividend yield on US stocks and 5-year nominal yields on US Treasury bonds. Correlations are computed for non-overlapping 5-year intervals over the period 1965:1-2011:4.

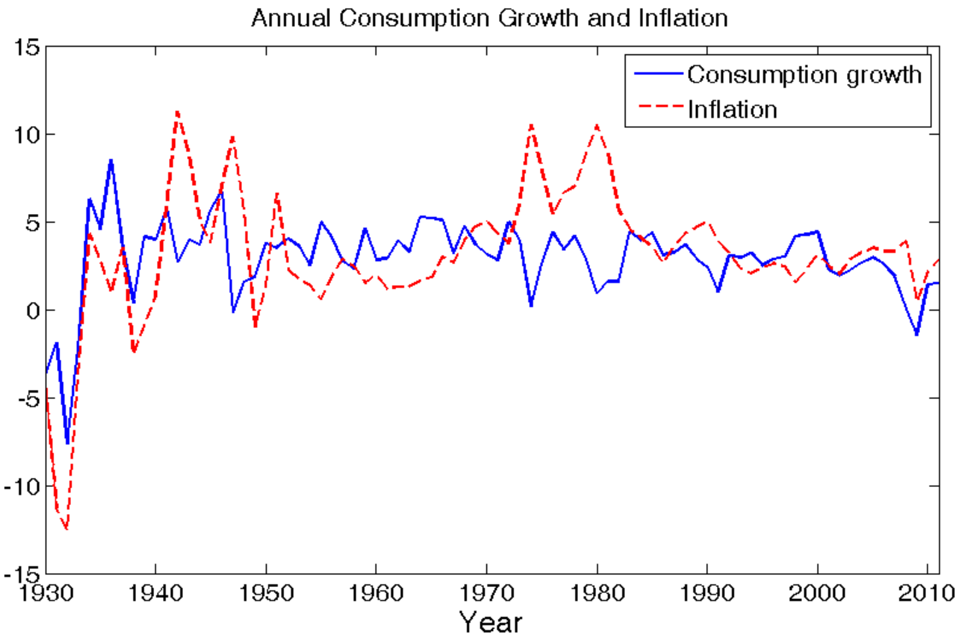


Figure 4. Annual real consumption growth and inflation over the period 1930-2011.

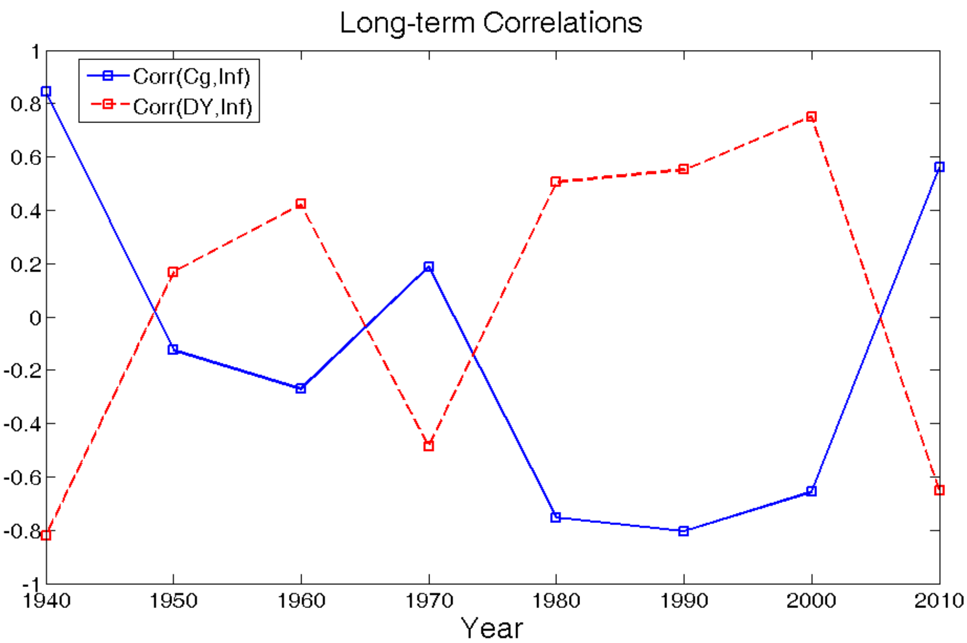


Figure 5. Correlations between annual real consumption growth and inflation and between dividend yields and inflation. Correlations are computed for non-overlapping 10-year intervals over the period 1930-2011.

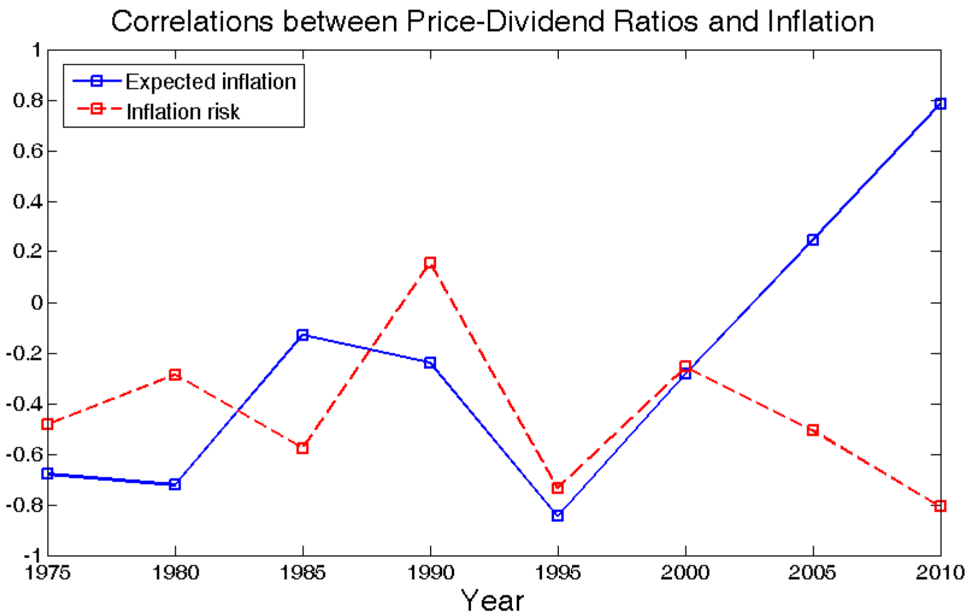


Figure 6. Correlations between log price-dividend ratios and expected inflation and inflation risk. Correlations are based on quarterly data and computed for non-overlapping 5-year intervals over the period 1970-2011. Inflation expectations are created by projecting quarterly inflation onto lagged growth, inflation, and yield spread. Inflation risk is measured as dispersion of inflation forecasts (PGDP) taken from Survey of Professional Forecasters.

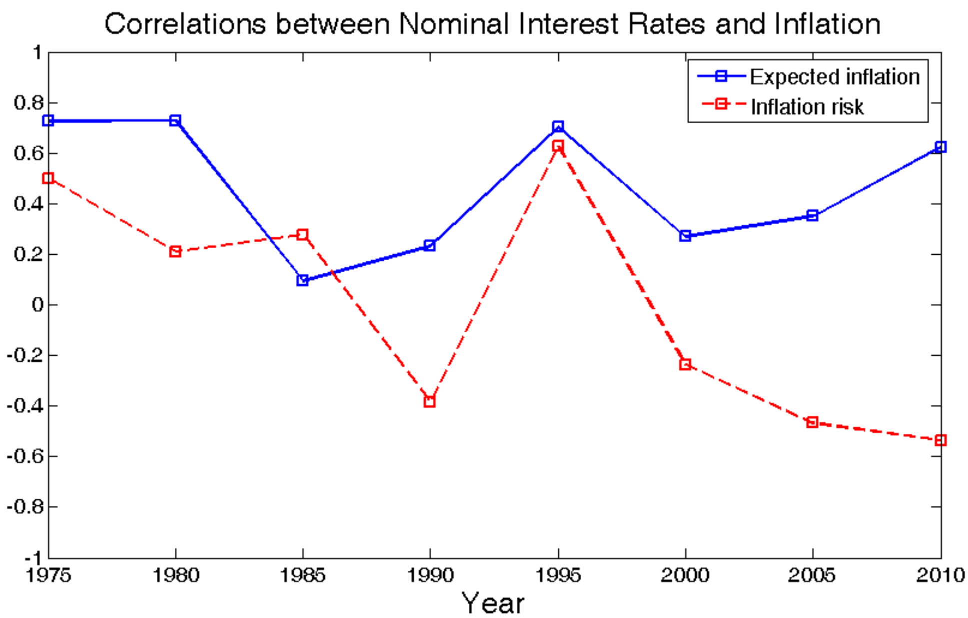


Figure 7. Correlations between the 5-year nominal interest rate and expected inflation and inflation risk. Correlations are based on quarterly data and computed for non-overlapping 5-year intervals over the period 1970-2011. Inflation expectations are created by projecting quarterly inflation onto lagged growth, inflation, and yield spread. Inflation risk is measured as dispersion of inflation forecasts (PGDP) taken from Survey of Professional Forecasters.

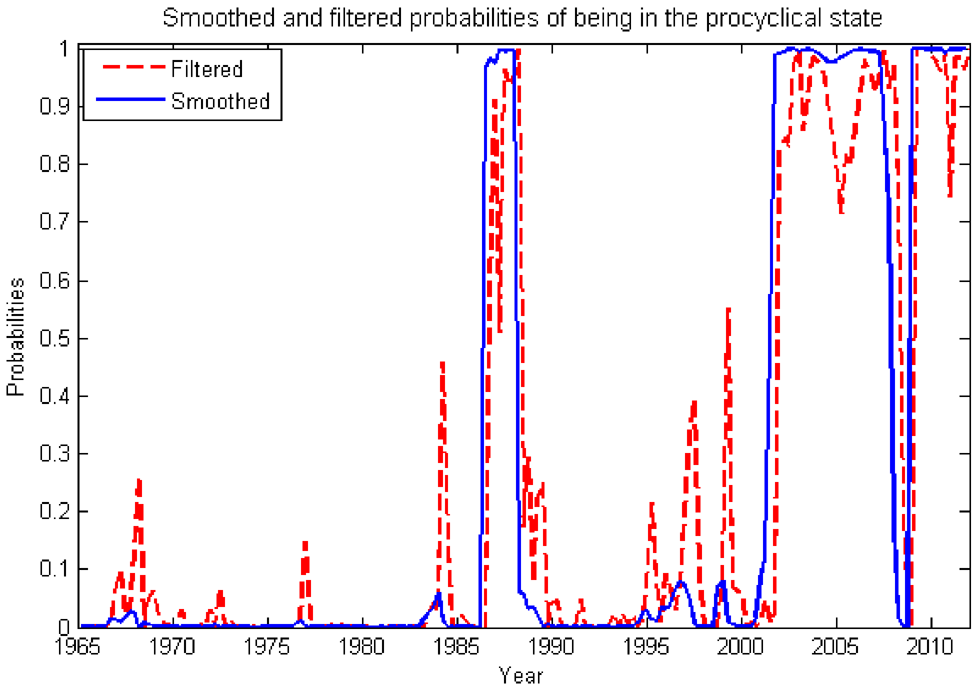


Figure 8. Filtered and smoothed probabilities of being in the procyclical inflation state. Probabilities are based on the estimated Markov-switching model described in Equation (1).

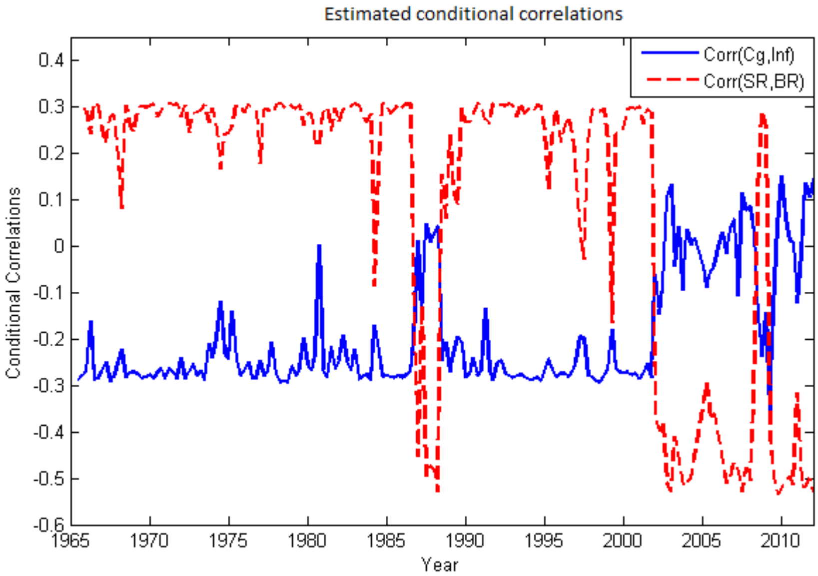


Figure 9. Empirically estimated quarterly conditional correlation between consumption growth and inflation and between stock and bond returns based on the estimated Markov-switching model described in Equation (1).

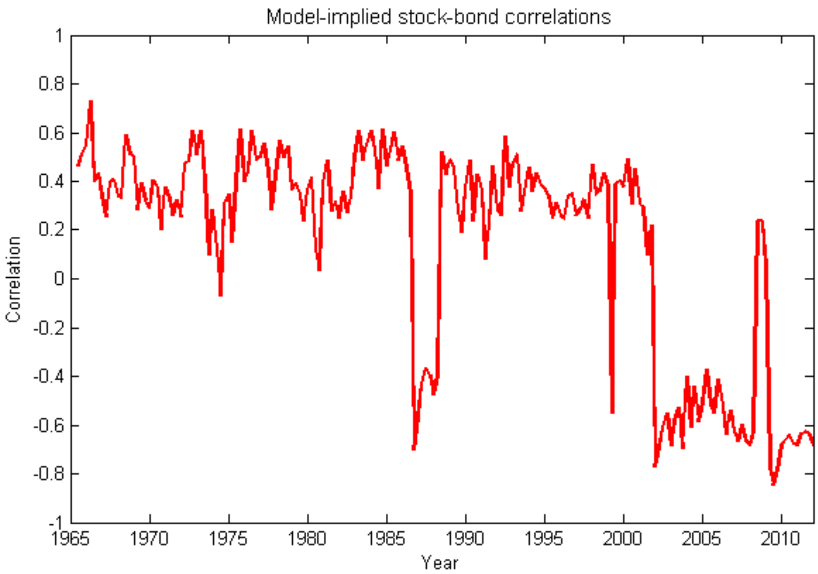


Figure 10. Model-implied quarterly conditional correlation between stock and 5-yr bond returns. Empirical proxies for the state variables, expected inflation and inflation volatility, are used to compute correlations. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. Inflation risk is measured as conditional inflation volatility based on an AR(1)-GARCH(1,1) on expected inflation. Correlations are computed using Equation (25) for the covariances together with analytical expressions for the volatility of stock and bond returns.

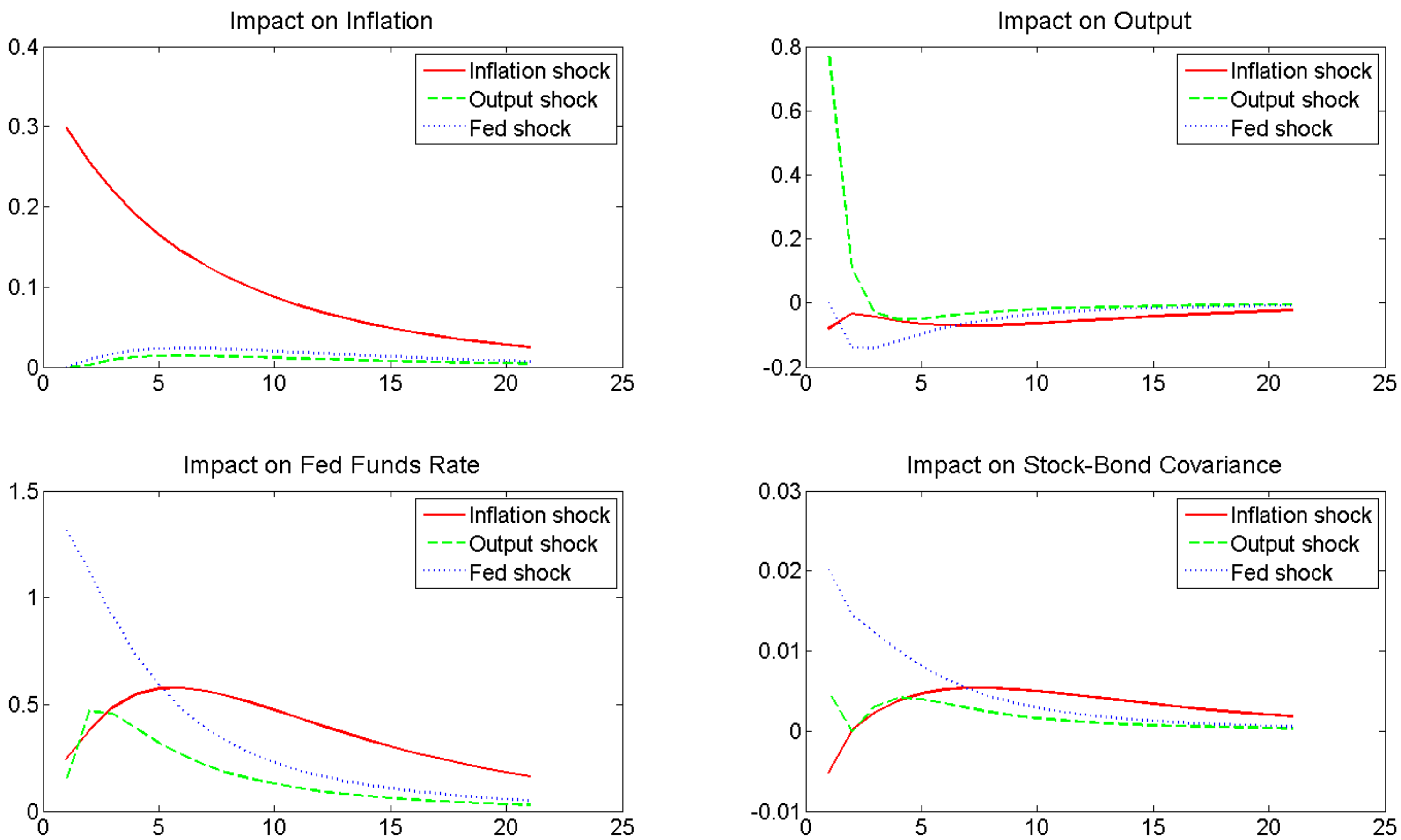


Figure 11. Impulse response functions for the countercyclical period 1965:1 - 1999:4. The shocks are retrieved from a VAR(1) with the ordering $X_t = [inflation, output, Fed\, funds\, rate, covariance]$ and where an orthogononalization is done using the Cholesky factor.

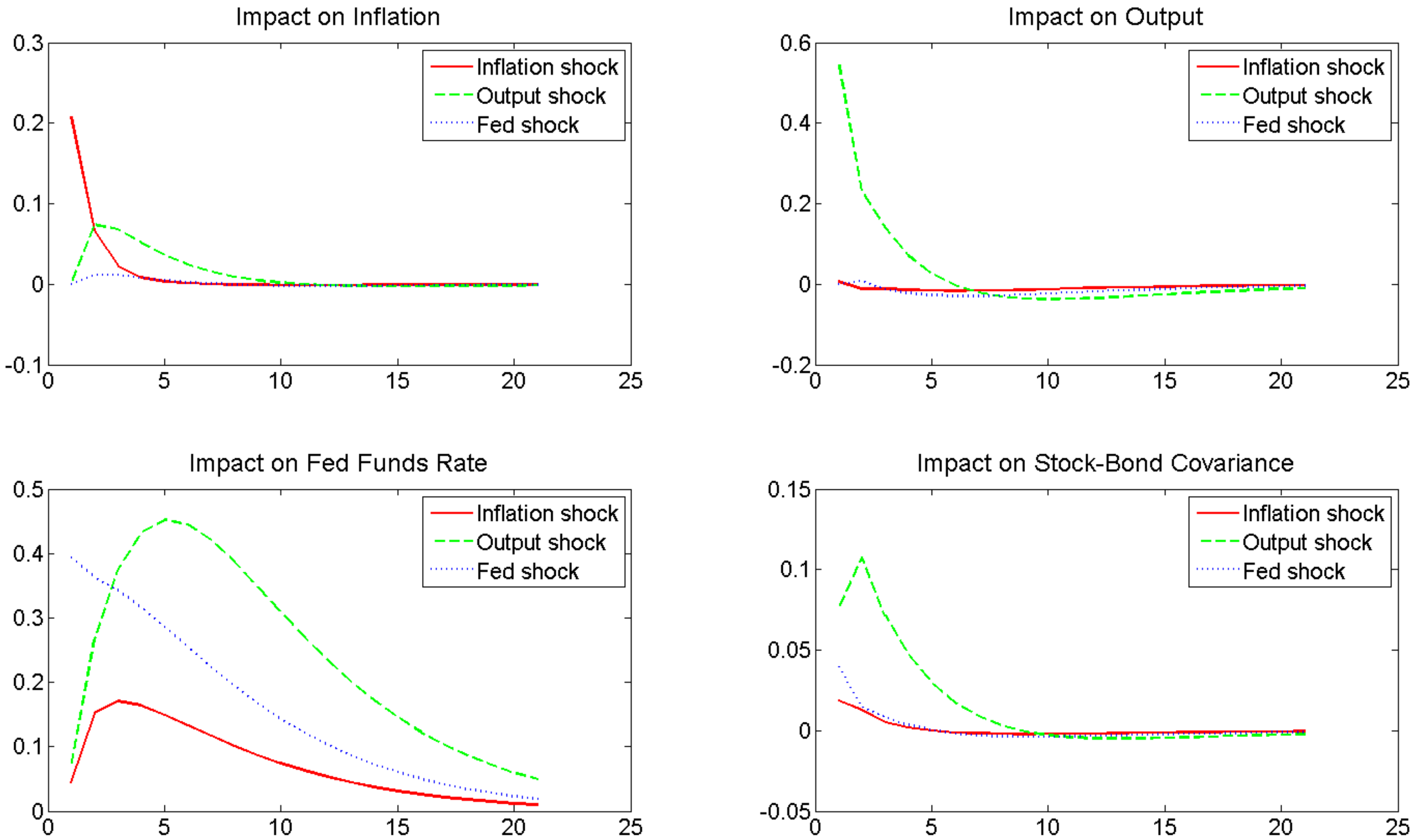


Figure 12. Impulse response functions for the procyclical period 2000:1 - 2011:4. The shocks are retrieved from a VAR(1) with the ordering $X_t = [inflation, output, Fed\, funds\, rate, covariance]$ and where an orthogononalization is done using the Cholesky factor.

APPENDIX

A Appendix I: The Model

A.1 Model Specification

The processes for log consumption growth ($\triangle c_{t+1}$), log inflation (π_{t+1}), log dividend growth ($\triangle d_{t+1}$) and variance of inflation ($\sigma^2_{\pi,t+1}$) are given by:

$$
\begin{aligned}
\Delta c_{t+1} &= \mu_c(s_{t+1}) + x_{c,t} + \sigma_c \eta_{c,t+1}, && (1)\\
\pi_{t+1} &= \mu_\pi(s_{t+1}) + x_{\pi,t} + \sigma_{\pi,t}\eta_{\pi,t+1}, && (2)\\
\triangle d_{t+1} &= \mu_d + \phi x_{c,t} + \varphi \sigma_c \eta_{d,t+1}, && (3)\\
\sigma^2_{\pi,t+1} &= \sigma^2_\pi + \upsilon_1(\sigma^2_{\pi,t} - \sigma^2_\pi) + \sigma_\upsilon w_{t+1}. && (4)
\end{aligned}
$$

The dynamics for the time-varying parts of the conditional means of the above processes are given by:

$$
\begin{aligned}
x_{c,t+1} &= \beta_1(s_{t+1})x_{c,t} + \beta_2(s_{t+1})x_{\pi,t} + \delta_1(s_{t+1})\sigma_c\varepsilon_{c,t+1} + \delta_2(s_{t+1})\sigma_{\pi,t}\varepsilon_{\pi,t+1}, && (5)\\
x_{\pi,t+1} &= \beta_4(s_{t+1})x_{\pi,t} + \delta_3(s_{t+1})\sigma_c\varepsilon_{c,t+1} + \delta_4(s_{t+1})\sigma_{\pi,t}\varepsilon_{\pi,t+1}. && (6)
\end{aligned}
$$

All shocks are mutually uncorrelated and i.i.d. normally distributed with a mean of zero and unit variance. $\beta_1(s_{t+1})$, $\beta_2(s_{t+1})$, $\beta_4(s_{t+1})$, $\delta_1(s_{t+1})$, $\delta_2(s_{t+1})$, $\delta_3(s_{t+1})$, and $\delta_4(s_{t+1})$, which govern the persistence of consumption and inflation shocks and their effect on the conditional mean of consumption growth and inflation, as well as the $\mu_c(s_{t+1})$ and $\mu_\pi(s_{t+1})$ depend on tomorrow's regime $s_{t+1} = (0,1)$. The probability of ending up in tomorrow's regime $s_{t+1} = (0,1)$ given today's regime $s_t = (0,1)$ is governed by the transition probability matrix of a Markov chain:

$$P = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix},$$

where $P(s_{t+1} = j|s_t = i) = p_{ij}$, $\sum_{j=0}^{1} p_{ij} = 1$ and $0 < p_{ij} < 1$. We assume that agents can observe the current regime.

The log IMRS for Epstein-Zin preferences can be written as:

$$m_{t+1}(s_{t+1}) = \theta ln(\delta) - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1) r_{c,t+1}(s_{t+1}). \tag{7}$$

A.2 Solving the Model

In the following Sections A.2.1 - A.2.4 we show how to solve the model using approximate analytical solutions.

A.2.1 The Price-Consumption Ratio

The log-return on the unobservable aggregate wealth portfolio is approximated as in Campbell and Shiller (1988):

$$r_{c,t+1}(s_{t+1}) = k_{c,0} + k_{c,1} pc_{t+1}(s_{t+1}) - pc_t(s_t) + \Delta c_{t+1}, \tag{8}$$

where pc_t denotes the log price-consumption ratio. The constants k_c are functions of the average level of pc_t, which we denote by $\bar{pc}$.[1]

[1] $k_{c,1} = \frac{\exp(\bar{pc})}{1+\exp(\bar{pc})}$ and $k_{c,0} = ln(1 + \exp(\bar{pc})) - k_{c,1}\bar{pc}$.

The log price-consumption ratio is conjectured to be a linear function of our state variables[2]:

$$pc_t(s_t) = A_{c,0}(s_t) + A_{c,1}(s_t)x_{c,t} + A_{c,2}(s_t)x_{\pi,t} + A_{c,3}(s_t)\sigma^2_{\pi,t}. \tag{9}$$

The A coefficients governing the price-consumption ratio can be derived using the log IMRS together with the given macro dynamics and the approximation for the return on the aggregate wealth portfolio. We will make use of the law of iterated expectations and of the Euler equation for the consumption asset, which can be written as:

$$E[\exp\{m_{t+1}(s_{t+1}) + r_{c,t+1}(s_{t+1})\}|I_t] = 1. \tag{10}$$

We first form expectations using the information set $I_{t+1} = \{x_{c,t}, x_{\pi,t}, \sigma^2_{\pi,t}, s_t, s_{t+1}\}$ and then condition them down by using the current information set $I_t = \{x_{c,t}, x_{\pi,t}, \sigma^2_{\pi,t}, s_t\}$. Using the law of iterated expectations, the Euler equation for the consumption asset can then be rewritten as:

$$\begin{aligned}
1 &= E[\exp\{m_{t+1}(s_{t+1}) + r_{c,t+1}(s_{t+1})\}|I_t] && (11)\\
&= E[E[\exp\{m_{t+1}(s_{t+1}) + r_{c,t+1}(s_{t+1})\}|I_{t+1}]|I_t] && (12)\\
&= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} E[\exp\{m_{t+1}(s_{t+1}) + r_{c,t+1}(s_{t+1})\}|I_{t+1}]. && (13)
\end{aligned}$$

Making use of the conditional normality (given I_{t+1}) of log consumption growth and the state variables (and therefore also $r_{c,t+1}$ and m_{t+1}) in a first step, and of the approximation $e^y - 1 \approx y$ in the second step[3], the above Euler condition can be restated as:

[2] Which are the time-varying conditional means of consumption growth and inflation and the time-varying conditional variance of inflation.
[3] This approximation has also been used in for example Bansal and Zhou (2002).

$$1=\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} \exp\{E[m_{t+1}(s_{t+1})+r_{c,t+1}(s_{t+1})|I_{t+1}]+\frac{1}{2}Var[m_{t+1}(s_{t+1})+r_{c,t+1}(s_{t+1})|I_{t+1}]\} \tag{14}$$

$$0=\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} \{E[m_{t+1}(s_{t+1})+r_{c,t+1}(s_{t+1})|I_{t+1}]+\frac{1}{2}Var[m_{t+1}(s_{t+1})+r_{c,t+1}(s_{t+1})|I_{t+1}]\}. \tag{15}$$

The conditional mean and the conditional variance in the above expression (15) are given by:

$$\begin{aligned}
E[m_{t+1}(s_{t+1})+r_{c,t+1}(s_{t+1})|I_{t+1}] &= \theta\ln(\delta)+\mu_c^{s_{t+1}}\overbrace{(\theta-\frac{\theta}{\psi})}^{=1-\gamma} \\
&+ \theta(k_{c,0}-A_{c,0}^{s_t}+k_{c,1}\{A_{c,0}^{s_{t+1}}+A_{c,3}^{s_{t+1}}\sigma_\pi^2[1-\upsilon_1]\}) \\
&+ x_{c,t}[(\theta-\frac{\theta}{\psi})+\theta(k_{c,1}A_{c,1}^{s_{t+1}}\beta_1^{s_{t+1}}-A_{c,1}^{s_t})] \\
&+ x_{\pi,t}[\theta(k_{c,1}A_{c,1}^{s_{t+1}}\beta_2^{s_{t+1}}+k_{c,1}A_{c,2}^{s_{t+1}}\beta_4^{s_{t+1}}-A_{c,2}^{s_t})] \\
&+ \sigma_{\pi,t}^2[\theta(k_{c,1}A_{c,3}^{s_{t+1}}\upsilon_1-A_{c,3}^{s_t})], \qquad (16)
\end{aligned}$$

$$Var[m_{t+1}(s_{t+1})+r_{c,t+1}(s_{t+1})|I_{t+1}] = \sigma_c^2X^{s_{t+1}}+\sigma_{\pi,t}^2Y^{s_{t+1}}+\sigma_\upsilon^2Z^{s_{t+1}}, \tag{17}$$

$$\begin{aligned}
X^{s_{t+1}} &= (\theta-\frac{\theta}{\psi})^2+(\theta k_{c,1}[A_{c,1}^{s_{t+1}}\delta_1^{s_{t+1}}+A_{c,2}^{s_{t+1}}\delta_3^{s_{t+1}}])^2, && (18)\\
Y^{s_{t+1}} &= (\theta k_{c,1}[A_{c,1}^{s_{t+1}}\delta_2^{s_{t+1}}+A_{c,2}^{s_{t+1}}\delta_4^{s_{t+1}}])^2, && (19)\\
Z^{s_{t+1}} &= (\theta k_{c,1}A_{c,3}^{s_{t+1}})^2. && (20)
\end{aligned}$$

Exploiting the fact that Equation (15) must hold for both starting regimes $s_t=(0,1)$ and for all values of our state variables gives us a system of 8 equations and 8 unknowns and allows us to solve for the A_c-coefficients:

$$A^0_{c,1} = (1-\frac{1}{\psi})\left[\frac{1+\beta^1_1 k_{c,1}(p_{01}-p_{11})}{(1-\beta^0_1 k_{c,1})(1-p_{11}\beta^1_1 k_{c,1})+p_{01}(\beta^0_1 k_{c,1}[1-\beta^1_1 k_{c,1}])}\right] \quad (21)$$

$$A^1_{c,1} = (1-\frac{1}{\psi})\left[\frac{1+\beta^0_1 k_{c,1}(p_{01}-p_{11})}{(1-\beta^0_1 k_{c,1})(1-p_{11}\beta^1_1 k_{c,1})+p_{01}(\beta^0_1 k_{c,1}[1-\beta^1_1 k_{c,1}])}\right] \quad (22)$$

$$A^0_{c,2} = \frac{\beta^1_2 A^1_{c,1} k_{c,1} p_{01} + \beta^0_2 A^0_{c,1} k_{c,1}[p_{00} + \beta^1_4 k_{c,1}(p_{01}-p_{11})]}{(1-\beta^0_4 k_{c,1}) + p_{01}[\beta^0_4 k_{c,1}(1-\beta^1_4 k_{c,1})] + p_{11}[\beta^1_4 k_{c,1}(\beta^0_4 k_{c,1}-1)]} \quad (23)$$

$$A^1_{c,2} = \frac{\beta^0_2 A^0_{c,1} k_{c,1} p_{10} + \beta^1_2 A^1_{c,1} k_{c,1}[p_{11} + \beta^0_4 k_{c,1}(p_{01}-p_{11})]}{(1-\beta^0_4 k_{c,1}) + p_{01}[\beta^0_4 k_{c,1}(1-\beta^1_4 k_{c,1})] + p_{11}[\beta^1_4 k_{c,1}(\beta^0_4 k_{c,1}-1)]} \quad (24)$$

$$A^0_{c,3} = \frac{1}{2}\frac{1}{\theta(1-k_{c,1}\upsilon_1)}[pY^{s_{t+1}=0} + (1-p)Y^{s_{t+1}=1}] \quad (25)$$

$$A^1_{c,3} = \frac{1}{2}\frac{1}{\theta(1-k_{c,1}\upsilon_1)}[PY^{s_{t+1}=0} + (1-P)Y^{s_{t+1}=1}], \quad (26)$$

with the probabilities p and P given by:

$$p = \frac{1-p_{01}+k_{c,1}\upsilon_1[p_{01}-p_{11}]}{1+k_{c,1}\upsilon_1[p_{01}-p_{11}]} \quad (27)$$

$$1-p = \frac{p_{01}}{1+k_{c,1}\upsilon_1[p_{01}-p_{11}]} \quad (28)$$

$$P = \frac{1-p_{11}}{1+k_{c,1}\upsilon_1[p_{01}-p_{11}]} \quad (29)$$

$$1-P = \frac{p_{11}+k_{c,1}\upsilon_1[p_{01}-p_{11}]}{1+k_{c,1}\upsilon_1[p_{01}-p_{11}]}. \quad (30)$$

$A^0_{c,0}$ and $A^0_{c,0}$ finally are given by:

$$A^0_{c,0} = \frac{1}{\theta(1-k_{c,1})}[\theta\ln(\delta) + \theta k_{c,0} + rW^{s_{t+1}=1} + (1-r)W^{s_{t+1}=0}] \quad (31)$$

$$A^1_{c,0} = \frac{1}{\theta(1-k_{c,1})}[\theta\ln(\delta) + \theta k_{c,0} + RW^{s_{t+1}=1} + (1-R)W^{s_{t+1}=0}], \quad (32)$$

where

$$W^{s_{t+1}=1} = \mu_c^1(\theta - \frac{\theta}{\psi}) + \theta k_{c,1} A_{c,3}^1 \sigma_\pi^2 [1-\upsilon_1] + \frac{1}{2}\sigma_\upsilon^2 Z^{s_{t+1}=1} + \frac{1}{2}\sigma_c^2 X^{s_{t+1}=1} \quad (33)$$

$$W^{s_{t+1}=0} = \mu_c^0(\theta - \frac{\theta}{\psi}) + \theta k_{c,1} A_{c,3}^0 \sigma_\pi^2 [1-\upsilon_1] + \frac{1}{2}\sigma_\upsilon^2 Z^{s_{t+1}=0} + \frac{1}{2}\sigma_c^2 X^{s_{t+1}=0}, \quad (34)$$

and

$$r = \frac{p_{01}}{1 + k_{c,1}[p_{01} - p_{11}]} \quad (35)$$

$$1 - r = \frac{1 + k_{c,1}[p_{01} - p_{11}] - p_{01}}{1 + k_{c,1}[p_{01} - p_{11}]} \quad (36)$$

$$R = \frac{k_{c,1}[p_{01} - p_{11}] + p_{11}}{1 + k_{c,1}[p_{01} - p_{11}]} \quad (37)$$

$$1 - R = \frac{1 - p_{11}}{1 + k_{c,1}[p_{01} - p_{11}]}. \quad (38)$$

A.2.2 The Price-Dividend Ratio

The coefficients governing the price-dividend ratio are found in an analogous manner as the coefficients for the price-consumption ratio above. The log-return on the market portfolio is again approximated as in Campbell and Shiller (1998) and the log price-dividend ratio again conjectured to be an affine function of our three state variables:

$$r_{m,t+1}(s_{t+1}) = k_{d,0} + k_{d,1} pd_{t+1}(s_{t+1}) - pd_t(s_t) + \Delta d_{t+1}, \quad (39)$$

$$pd_t(s_t) = A_{d,0}(s_t) + A_{d,1}(s_t) x_{c,t} + A_{d,2}(s_t) x_{\pi,t} + A_{d,3}(s_t) \sigma_{\pi,t}^2, \quad (40)$$

with pd_t denoting the log price-dividend ratio. The constants k_d are functions of the average level of pd_t, which we denote by $\bar{pd}$.[4]

The Euler condition for the market return is analogous to Equation (15):

$$0 = \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} \{E[m_{t+1}(s_{t+1}) + r_{m,t+1}(s_{t+1})|I_{t+1}] + \frac{1}{2} Var[m_{t+1}(s_{t+1}) + r_{m,t+1}(s_{t+1})|I_{t+1}]\} \tag{41}$$

with conditional mean and variance on the above expressions given by:

$$\begin{aligned}
E[m_{t+1}(s_{t+1}) + r_{m,t+1}(s_{t+1})|I_{t+1}] &= \theta \ln(\delta) + \mu_c^{s_{t+1}} \overbrace{(\theta - \frac{\theta}{\psi} - 1)}^{=-\gamma} + (\theta - 1)(k_{c,0} - A_{c,0}^{s_t} \\
&+ k_{c,1}\{A_{c,0}^{s_{t+1}} + A_{c,3}^{s_{t+1}} \sigma_\pi^2 [1 - \upsilon_1]\}) + k_{d,0} \\
&+ k_{d,1}\{A_{d,0}^{s_{t+1}} + A_{d,3}^{s_{t+1}} \sigma_\pi^2 [1 - \upsilon_1]\} - A_{d,0}^{s_t} + \mu_d^{s_{t+1}} \\
&+ x_{c,t}[\phi - \gamma + (\theta - 1)(k_{c,1} A_{c,1}^{s_{t+1}} \beta_1^{s_{t+1}} - A_{c,1}^{s_t}) \\
&+ k_{d,1} A_{d,1}^{s_{t+1}} \beta_1^{s_{t+1}} - A_{d,1}^{s_t}] \\
&+ x_{\pi,t}[(\theta - 1)(k_{c,1} A_{c,1}^{s_{t+1}} \beta_2^{s_{t+1}} + k_{c,1} A_{c,2}^{s_{t+1}} \beta_4^{s_{t+1}} - A_{c,2}^{s_t}) \\
&+ k_{d,1} A_{d,1}^{s_{t+1}} \beta_2^{s_{t+1}} + k_{d,1} A_{d,2}^{s_{t+1}} \beta_4^{s_{t+1}} - A_{d,2}^{s_t}] \\
&+ \sigma_{\pi,t}^2 [(\theta - 1)(k_{c,1} A_{c,3}^{s_{t+1}} \upsilon_1 - A_{c,3}^{s_t}) + k_{d,1} A_{d,3}^{s_{t+1}} \upsilon_1 \\
&- A_{d,3}^{s_t}], \qquad (42)
\end{aligned}$$

$$Var[m_{t+1}(s_{t+1}) + r_{m,t+1}(s_{t+1})|I_{t+1}] = \sigma_c^2 X^{s_{t+1}} + \sigma_{\pi,t}^2 Y^{s_{t+1}} + \sigma_\upsilon^2 Z^{s_{t+1}}, \tag{43}$$

[4] $k_{d,1} = \frac{\exp(\bar{pd})}{1+\exp(\bar{pd})}$ and $k_{d,0} = ln(1 + \exp(\bar{pd})) - k_{d,1}\bar{pd}$.

$$X^{s_{t+1}} = \gamma^2 + \varphi^2 + \{(\theta-1)k_{c,1}[A_{c,1}^{s_{t+1}}\delta_1^{s_{t+1}} + A_{c,2}^{s_{t+1}}\delta_3^{s_{t+1}}] + k_{d,1}[A_{d,1}^{s_{t+1}}\delta_1^{s_{t+1}} + A_{d,2}^{s_{t+1}}\delta_3^{s_{t+1}}]\}^2 \quad (44)$$

$$Y^{s_{t+1}} = [(\theta-1)k_{c,1}(A_{c,1}^{s_{t+1}}\delta_2^{s_{t+1}} + A_{c,2}^{s_{t+1}}\delta_4^{s_{t+1}}) + k_{d,1}(A_{d,1}^{s_{t+1}}\delta_2^{s_{t+1}} + A_{d,2}^{s_{t+1}}\delta_4^{s_{t+1}})]^2 \quad (45)$$

$$Z^{s_{t+1}} = [(\theta-1)k_{c,1}A_{c,3}^{s_{t+1}} + k_{d,1}A_{d,3}^{s_{t+1}}]^2. \quad (46)$$

Exploiting again the fact that the Euler Equation (41) must hold for both starting regimes $s_t = (0,1)$ and for all values of our state variables allows us to solve for the A_d-coefficients:

$$A_{d,1}^0 = (\phi - \frac{1}{\psi})\left[\frac{1+\beta_1^1 k_{d,1}(p_{01}-p_{11})}{(1-\beta_1^0 k_{d,1})(1-p_{11}\beta_1^1 k_{d,1}) + p_{01}(\beta_1^0 k_{d,1}[1-\beta_1^1 k_{d,1}])}\right] \quad (47)$$

$$A_{d,1}^1 = (\phi - \frac{1}{\psi})\left[\frac{1+\beta_1^0 k_{d,1}(p_{01}-p_{11})}{(1-\beta_1^0 k_{d,1})(1-p_{11}\beta_1^1 k_{d,1}) + p_{01}(\beta_1^0 k_{d,1}[1-\beta_1^1 k_{d,1}])}\right] \quad (48)$$

$$A_{d,2}^0 = \frac{\beta_2^1 A_{d,1}^1 k_{d,1} p_{01} + \beta_2^0 A_{d,1}^0 k_{d,1}[p_{00} + \beta_4^1 k_{d,1}(p_{01}-p_{11})]}{(1-\beta_4^0 k_{d,1}) + p_{01}[\beta_4^0 k_{d,1}(1-\beta_4^1 k_{d,1})] + p_{11}[\beta_4^1 k_{d,1}(\beta_4^0 k_{d,1}-1)]} \quad (49)$$

$$A_{d,2}^1 = \frac{\beta_2^0 A_{d,1}^0 k_{d,1} p_{10} + \beta_2^1 A_{d,1}^1 k_{d,1}[p_{11} + \beta_4^0 k_{d,1}(p_{01}-p_{11})]}{(1-\beta_4^0 k_{d,1}) + p_{01}[\beta_4^0 k_{d,1}(1-\beta_4^1 k_{d,1})] + p_{11}[\beta_4^1 k_{d,1}(\beta_4^0 k_{d,1}-1)]} \quad (50)$$

$$A_{d,3}^0 = \frac{1}{1-k_{d,1}\upsilon_1}[p_1V_1 + p_2V_2 + p_3V_3 + p_4V_4] \quad (51)$$

$$A_{d,3}^1 = \frac{1}{1-k_{d,1}\upsilon_1}[P_1V_1 + P_2V_2 + P_3V_3 + P_4V_4] \quad (52)$$

$$V_1 = (\theta-1)(k_{c,1}A_{c,3}^1\upsilon_1 - A_{c,3}^0) + \frac{1}{2}Y^{s_{t+1}=1} \quad (53)$$

$$V_2 = (\theta-1)(k_{c,1}A_{c,3}^0\upsilon_1 - A_{c,3}^0) + \frac{1}{2}Y^{s_{t+1}=0} \quad (54)$$

$$V_3 = (\theta-1)(k_{c,1}A_{c,3}^1\upsilon_1 - A_{c,3}^1) + \frac{1}{2}Y^{s_{t+1}=1} \quad (55)$$

$$V_4 = (\theta-1)(k_{c,1}A_{c,3}^0\upsilon_1 - A_{c,3}^1) + \frac{1}{2}Y^{s_{t+1}=0} \quad (56)$$

$$1 = p_1 + p_2 + p_3 + p_4 \quad (57)$$

$$1 = P_1 + P_2 + P_3 + P_4, \quad (58)$$

with $Y^{s_{t+1}}$ as in (45) and the probabilities p_l and P_l given by:

$$
\begin{aligned}
p_1 &= \frac{p_{01}(1-k_{d,1}p_{11}\upsilon_1)}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (59)\\
p_2 &= \frac{(1-p_{01})(1-k_{d,1}p_{11}\upsilon_1)}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (60)\\
p_3 &= \frac{p_{11}p_{01}k_{d,1}\upsilon_1}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (61)\\
p_4 &= \frac{(1-p_{11})p_{01}k_{d,1}\upsilon_1}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (62)\\
P_1 &= \frac{(1-p_{11})p_{01}k_{d,1}\upsilon_1}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (63)\\
P_2 &= \frac{(1-p_{11})(1-p_{01})k_{d,1}\upsilon_1}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (64)\\
P_3 &= \frac{p_{11}(1-k_{d,1}\upsilon_1[1-p_{01}])}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]} && (65)\\
P_4 &= \frac{(1-p_{11})(1-k_{d,1}\upsilon_1[1-p_{01}])}{1+k_{d,1}\upsilon_1[p_{01}-p_{11}]}. && (66)
\end{aligned}
$$

$A^0_{d,0}$ and $A^1_{d,0}$ finally are given by:

$$
\begin{aligned}
A^0_{d,0} &= \frac{1}{1-k_{d,1}}\{(1-\theta)[r_1A^1_{c,0}+(1-r_1)A^0_{c,0}]+r_2V^{s_{t+1}=0}+(1-r_2)V^{s_{t+1}=1}\} && (67)\\
A^1_{d,0} &= \frac{1}{1-k_{d,1}}\{(1-\theta)[R_1A^1_{c,0}+(1-R_1)A^0_{c,0}]+R_2V^{s_{t+1}=0}+(1-R_2)V^{s_{t+1}=1}\}, && (68)
\end{aligned}
$$

where

$$
\begin{aligned}
V^{s_{t+1}=0} &= \theta\ln(\delta)-\gamma\mu^0_c+(\theta-1)(k_{c,0}+k_{c,1}[A^0_{c,0}+A^0_{c,3}\sigma^2_\pi(1-\upsilon_1)])+k_{d,0}\\
&+ k_{d,1}A^0_{d,3}\sigma^2_\pi(1-\upsilon_1)+\mu_d+\frac{1}{2}\sigma^2_cX^{s_{t+1}=0}+\frac{1}{2}\sigma^2_\upsilon Z^{s_{t+1}=0} && (69)\\
V^{s_{t+1}=1} &= \theta\ln(\delta)-\gamma\mu^1_c+(\theta-1)(k_{c,0}+k_{c,1}[A^1_{c,0}+A^1_{c,3}\sigma^2_\pi(1-\upsilon_1)])+k_{d,0}\\
&+ k_{d,1}A^1_{d,3}\sigma^2_\pi(1-\upsilon_1)+\mu_d+\frac{1}{2}\sigma^2_cX^{s_{t+1}=1}+\frac{1}{2}\sigma^2_\upsilon Z^{s_{t+1}=1}, && (70)
\end{aligned}
$$

with $X^{s_{t+1}}$ and $Z^{s_{t+1}}$ as in (44) and (46) and probabilities given by:

$$
\begin{aligned}
r_1 &= \frac{k_{d,1}p_{01}}{1+k_{d,1}[p_{01}-p_{11}]} && (71)\\
1-r_1 &= \frac{1-k_{d,1}p_{11}}{1+k_{d,1}[p_{01}-p_{11}]} && (72)\\
r_2 &= \frac{1+k_{d,1}[p_{01}-p_{11}]-p_{01}}{1+k_{d,1}[p_{01}-p_{11}]} && (73)\\
1-r_2 &= \frac{p_{01}}{1+k_{d,1}[p_{01}-p_{11}]} && (74)\\
R_1 &= \frac{1+k_{d,1}[p_{01}-1]}{1+k_{d,1}[p_{01}-p_{11}]} && (75)\\
1-R_1 &= \frac{k_{d,1}(1-p_{11})}{1+k_{d,1}[p_{01}-p_{11}]} && (76)\\
R_2 &= \frac{1-p_{11}}{1+k_{d,1}[p_{01}-p_{11}]} && (77)\\
1-R_2 &= \frac{k_{d,1}[p_{01}-p_{11}]+p_{11}}{1+k_{d,1}[p_{01}-p_{11}]}. && (78)
\end{aligned}
$$

A.2.3 Real Bonds

Let $y_{t,n} = -\frac{1}{n}q_{t,n}$ denote the n-period log real yield with $q_{t,n}$ being the log price at time t of a real bond with maturity of n periods (t and n both are expressed in quarters). $q_{t,n}$ is conjectured to be a linear function of our three state variables:

$$q_{t,n}(s_t) = D_{0,n}(s_t) + D_{1,n}(s_t)x_{c,t} + D_{2,n}(s_t)x_{\pi,t} + D_{3,n}(s_t)\sigma^2_{\pi,t}. \tag{79}$$

The Euler equation for real bonds is:

$$1 = E[\exp\{m_{t+1}(s_{t+1}) + q_{t+1,n-1}(s_{t+1}) - q_{t,n}(s_t)\}|I_t]. \tag{80}$$

Making use of the law of iterated expectations and of the conditional normality of log consumption growth and the state variables and of the approximation $e^y - 1 \approx y$ analogous to Sections A.2.1 and A.2.2, the Euler equation for real bonds can be rewritten as:

$$\begin{aligned} q_{t,n}(s_t) &= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} \{E[m_{t+1}(s_{t+1}) + q_{t+1,n-1}(s_{t+1})|I_{t+1}] \\ &+ \frac{1}{2} Var[m_{t+1}(s_{t+1}) + q_{t+1,n-1}(s_{t+1})|I_{t+1}]\}. \end{aligned} \tag{81}$$

The conditional mean and the conditional variance in the above expression (81) are given by:

$$\begin{aligned} E[m_{t+1}(s_{t+1}) + q_{t+1,n-1}(s_{t+1})|I_{t+1}] = {} & \theta \ln(\delta) + \mu_c^{s_{t+1}} \overbrace{(\theta - 1 - \frac{\theta}{\psi})}^{=-\gamma} + (\theta-1)(k_{c,0} - A_{c,0}^{s_t} \\ & + k_{c,1}\{A_{c,0}^{s_{t+1}} + A_{c,3}^{s_{t+1}} \sigma_\pi^2 (1-\upsilon_1)\}) + D_{0,n-1}^{s_{t+1}} \\ & + D_{3,n-1}^{s_{t+1}} \sigma_\pi^2 (1-\upsilon_1) \\ & + x_{c,t}[-\gamma + (\theta-1)(k_{c,1} A_{c,1}^{s_{t+1}} \beta_1^{s_{t+1}} - A_{c,1}^{s_t}) + D_{1,n-1}^{s_{t+1}} \beta_1^{s_{t+1}}] \\ & + x_{\pi,t}[(\theta-1)(k_{c,1} A_{c,1}^{s_{t+1}} \beta_2^{s_{t+1}} + k_{c,1} A_{c,2}^{s_{t+1}} \beta_4^{s_{t+1}} - A_{c,2}^{s_t}) \\ & + D_{1,n-1}^{s_{t+1}} \beta_2^{s_{t+1}} + D_{2,n-1}^{s_{t+1}} \beta_4^{s_{t+1}}] \\ & + \sigma_{\pi,t}^2[(\theta-1)(k_{c,1} A_{c,3}^{s_{t+1}} \upsilon_1 - A_{c,3}^{s_t}) + D_{3,n-1}^{s_{t+1}} \upsilon_1], \end{aligned} \tag{82}$$

$$Var[m_{t+1}(s_{t+1}) + q_{t+1,n-1}(s_{t+1})|I_{t+1}] = \sigma_c^2 X_{n-1}^{s_{t+1}} + \sigma_{\pi,t}^2 Y_{n-1}^{s_{t+1}} + \sigma_v^2 Z_{n-1}^{s_{t+1}}, \tag{83}$$

$$X_{n-1}^{s_{t+1}} = \gamma^2 + [(\theta-1)(k_{c,1} A_{c,1}^{s_{t+1}} \delta_1^{s_{t+1}} + k_{c,1} A_{c,2}^{s_{t+1}} \delta_3^{s_{t+1}}) + D_{1,n-1}^{s_{t+1}} \delta_1^{s_{t+1}} + D_{2,n-1}^{s_{t+1}} \delta_3^{s_{t+1}}]^2 \tag{84}$$

$$Y_{n-1}^{s_{t+1}} = [(\theta-1)(k_{c,1} A_{c,1}^{s_{t+1}} \delta_2^{s_{t+1}} + k_{c,1} A_{c,2}^{s_{t+1}} \delta_4^{s_{t+1}}) + D_{1,n-1}^{s_{t+1}} \delta_2^{s_{t+1}} + D_{2,n-1}^{s_{t+1}} \delta_4^{s_{t+1}}]^2 \tag{85}$$

$$Z_{n-1}^{s_{t+1}} = [(\theta-1) k_{c,1} A_{c,3}^{s_{t+1}} + D_{3,n-1}^{s_{t+1}}]^2. \tag{86}$$

Exploiting the fact that Equation (81) must hold for both starting regimes $s_t = (0,1)$ and for all values of our state variables and that $D_{i,0} = 0$ for $i = 0,1,2,3$, allows us to solve for the D-coefficients:

$$
\begin{aligned}
D^0_{1,n} &= -\frac{1}{\psi} + p_{00} D^0_{1,n-1}\beta^0_1 + p_{01} D^1_{1,n-1}\beta^1_1 && (87)\\
D^1_{1,n} &= -\frac{1}{\psi} + p_{10} D^0_{1,n-1}\beta^0_1 + p_{11} D^1_{1,n-1}\beta^1_1 && (88)\\
D^0_{2,n} &= p_{00}[D^0_{1,n-1}\beta^0_2 + D^0_{2,n-1}\beta^0_4] + p_{01}[D^1_{1,n-1}\beta^1_2 + D^1_{2,n-1}\beta^1_4] && (89)\\
D^1_{2,n} &= p_{11}[D^1_{1,n-1}\beta^1_2 + D^1_{2,n-1}\beta^1_4] + p_{10}[D^0_{1,n-1}\beta^0_2 + D^0_{2,n-1}\beta^0_4] && (90)\\
D^0_{3,n} &= p_{00}[(\theta-1)A^0_{c,3}(k_{c,1}\upsilon_1 - 1) + D^0_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=0}]\\
&+ p_{01}[(\theta-1)(k_{c,1}\upsilon_1 A^1_{c,3} - A^0_{c,3}) + D^1_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=1}] && (91)\\
D^1_{3,n} &= p_{11}[(\theta-1)A^1_{c,3}(k_{c,1}\upsilon_1 - 1) + D^1_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=1}]\\
&+ p_{10}[(\theta-1)(k_{c,1}\upsilon_1 A^0_{c,3} - A^1_{c,3}) + D^0_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=0}]. && (92)
\end{aligned}
$$

$D^0_{0,n}$ and $D^1_{0,n}$ finally are given by:

$$
\begin{aligned}
D^0_{0,n} &= p_{00}[(\theta\ln(\delta) - \gamma\mu^0_c + (\theta-1)(k_{c,0} - A^0_{c,0} + k_{c,1}A^0_{c,0} + k_{c,1}A^0_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^0_{0,n-1}\\
&+ D^0_{3,n-1}\sigma^2_\pi(1-\upsilon_1) + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=0} + \sigma^2_c X^{s_{t+1}=0})]\\
&+ p_{01}[\theta\ln(\delta) - \gamma\mu^1_c + (\theta-1)(k_{c,0} - A^0_{c,0} + k_{c,1}A^1_{c,0} + k_{c,1}A^1_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^1_{0,n-1}\\
&+ D^1_{3,n-1}\sigma^2_\pi(1-\upsilon_1) + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=1} + \sigma^2_c X^{s_{t+1}=1})] && (93)\\
D^1_{0,n} &= p_{11}[\theta\ln(\delta) - \gamma\mu^1_c + (\theta-1)(k_{c,0} - A^1_{c,0} + k_{c,1}A^1_{c,0} + k_{c,1}A^1_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^1_{0,n-1}\\
&+ D^1_{3,n-1}\sigma^2_\pi(1-\upsilon_1) + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=1} + \sigma^2_c X^{s_{t+1}=1})]\\
&+ p_{10}[\theta\ln(\delta) - \gamma\mu^0_c + (\theta-1)(k_{c,0} - A^1_{c,0} + k_{c,1}A^0_{c,0} + k_{c,1}A^0_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^0_{0,n-1}\\
&+ D^0_{3,n-1}\sigma^2_\pi(1-\upsilon_1) + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=0} + \sigma^2_c X^{s_{t+1}=0})]. && (94)
\end{aligned}
$$

A.2.4 Nominal Bonds

Let $y^{\$}_{t,n} = -\frac{1}{n}q^{\$}_{t,n}$ denote the n-period log nominal yield with $q^{\$}_{t,n}$ being the log price at time t of a nominal bond with maturity of n periods. $q^{\$}_{t,n}$ is conjectured to be a linear function of our state variables:

$$q^{\$}_{t,n}(s_t) = D^{\$}_{0,n}(s_t) + D^{\$}_{1,n}(s_t)x_{c,t} + D^{\$}_{2,n}(s_t)x_{\pi,t} + D^{\$}_{3,n}(s_t)\sigma^2_{\pi,t}. \tag{95}$$

The Euler equation for nominal bonds is:

$$1 = E[\exp\{m_{t+1}(s_{t+1}) + q^{\$}_{t+1,n-1}(s_{t+1}) - q^{\$}_{t,n}(s_t) - \pi_{t+1}\}|I_t]. \tag{96}$$

Making use of the law of iterated expectations, the conditional normality of log consumption growth and the state variables and of the approximation $e^y - 1 \approx y$ analogous to Sections A.2.1 and A.2.2, the Euler equation for nominal bonds can be rewritten as:

$$\begin{aligned} q^{\$}_{t,n}(s_t) &= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}}\{E[m_{t+1}(s_{t+1}) - \pi_{t+1} + q^{\$}_{t+1,n-1}(s_{t+1})|I_{t+1}] \\ &+ \frac{1}{2}Var[m_{t+1}(s_{t+1}) - \pi_{t+1} + q^{\$}_{t+1,n-1}(s_{t+1})|I_{t+1}]\}. \end{aligned} \tag{97}$$

The conditional mean and the conditional variance in the above expression (97) are given by:

$$
\begin{aligned}
E[m_{t+1}(s_{t+1}) - \pi_{t+1} + q^{\$}_{t+1,n-1}(s_{t+1})|I_{t+1}] &= [\theta \ln(\delta) - \mu_c^{s_{t+1}}\gamma + (\theta-1)(k_{c,0} - A^{s_t}_{c,0} \\
&+ k_{c,1}\{A^{s_{t+1}}_{c,0} + A^{s_{t+1}}_{c,3}\sigma^2_\pi(1-\upsilon_1)\}) \\
&+ D^{\$ s_{t+1}}_{0,n-1} + D^{\$ s_{t+1}}_{3,n-1}\sigma^2_\pi(1-\upsilon_1) - \mu_\pi^{s_{t+1}}] \\
&+ x_{c,t}[-\gamma + (\theta-1)(k_{c,1}A^{s_{t+1}}_{c,1}\beta_1^{s_{t+1}} - A^{s_t}_{c,1}) \\
&+ D^{\$ s_{t+1}}_{1,n-1}\beta_1^{s_{t+1}}] \\
&+ x_{\pi,t}[(\theta-1)(k_{c,1}A^{s_{t+1}}_{c,1}\beta_2^{s_{t+1}} + k_{c,1}A^{s_{t+1}}_{c,2}\beta_4^{s_{t+1}} \\
&- A^{s_t}_{c,2}) + D^{\$ s_{t+1}}_{1,n-1}\beta_2^{s_{t+1}} + D^{\$ s_{t+1}}_{2,n-1}\beta_4^{s_{t+1}} - 1] \\
&+ \sigma^2_{\pi,t}[(\theta-1)(k_{c,1}A^{s_{t+1}}_{c,3}\upsilon_1 - A^{s_t}_{c,3}) \\
&+ D^{\$ s_{t+1}}_{3,n-1}\upsilon_1], \qquad (98)
\end{aligned}
$$

$$
Var[m_{t+1}(s_{t+1}) - \pi_{t+1} + q^{\$}_{t+1,n-1}(s_{t+1})|I_{t+1}] = \sigma^2_c X^{s_{t+1}}_{n-1} + \sigma^2_{\pi,t} Y^{s_{t+1}}_{n-1} + \sigma^2_\upsilon Z^{s_{t+1}}_{n-1}, \qquad (99)
$$

$$
\begin{aligned}
X^{s_{t+1}}_{n-1} &= \gamma^2 + [(\theta-1)(k_{c,1}A^{s_{t+1}}_{c,1}\delta_1^{s_{t+1}} + k_{c,1}A^{s_{t+1}}_{c,2}\delta_3^{s_{t+1}}) + D^{\$ s_{t+1}}_{1,n-1}\delta_1^{s_{t+1}} + D^{\$ s_{t+1}}_{2,n-1}\delta_3^{s_{t+1}}]^2 \qquad (100) \\
Y^{s_{t+1}}_{n-1} &= [(\theta-1)(k_{c,1}A^{s_{t+1}}_{c,1}\delta_2^{s_{t+1}} + k_{c,1}A^{s_{t+1}}_{c,2}\delta_4^{s_{t+1}}) + D^{\$ s_{t+1}}_{1,n-1}\delta_2^{s_{t+1}} + D^{\$ s_{t+1}}_{2,n-1}\delta_4^{s_{t+1}}]^2 + 1 \qquad (101) \\
Z^{s_{t+1}}_{n-1} &= [(\theta-1)k_{c,1}A^{s_{t+1}}_{c,3} + D^{\$ s_{t+1}}_{3,n-1}]^2. \qquad (102)
\end{aligned}
$$

Exploiting the fact that Equation (97) must hold for both starting regimes $s_t = (0,1)$ and for all values of our state variables and that $D^{\$}_{i,0} = 0$ for $i = 0,1,2,3$ allows us to solve a system of 8 equations for the 8 unknown $D^{\$}$-coefficients:

$$
\begin{aligned}
D^{\$0}_{1,n} &= -\frac{1}{\psi} + p_{00} D^{\$0}_{1,n-1}\beta^0_1 + p_{01} D^{\$1}_{1,n-1}\beta^1_1 && (103)\\
D^{\$1}_{1,n} &= -\frac{1}{\psi} + p_{10} D^{\$0}_{1,n-1}\beta^0_1 + p_{11} D^{\$1}_{1,n-1}\beta^1_1 && (104)\\
D^{\$0}_{2,n} &= p_{00}[D^{\$0}_{1,n-1}\beta^0_2 + D^{\$0}_{2,n-1}\beta^0_4] + p_{01}[D^{\$1}_{1,n-1}\beta^1_2 + D^{\$1}_{2,n-1}\beta^1_4] - 1 && (105)\\
D^{\$1}_{2,n} &= p_{11}[D^{\$1}_{1,n-1}\beta^1_2 + D^{\$1}_{2,n-1}\beta^1_4] + p_{10}[D^{\$0}_{1,n-1}\beta^0_2 + D^{\$0}_{2,n-1}\beta^0_4] - 1 && (106)\\
D^{\$0}_{3,n} &= p_{00}[(\theta-1)(A^0_{c,3}k_{c,1}\upsilon_1 - A^0_{c,3}) + D^{\$0}_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=0}] \\
&+ p_{01}[(\theta-1)(k_{c,1}\upsilon_1 A^1_{c,3} - A^0_{c,3}) + D^{\$1}_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=1}] && (107)\\
D^{\$1}_{3,n} &= p_{11}[(\theta-1)(A^1_{c,3}k_{c,1}\upsilon_1 - A^1_{c,3}) + D^{\$1}_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=1}] \\
&+ p_{10}[(\theta-1)(k_{c,1}\upsilon_1 A^0_{c,3} - A^1_{c,3}) + D^{\$0}_{3,n-1}\upsilon_1 + \frac{1}{2}Y^{s_{t+1}=0}]. && (108)
\end{aligned}
$$

$D^{\$0}_{0,n}$ and $D^{\$1}_{0,n}$ finally are given by:

$$
\begin{aligned}
D^{\$0}_{0,n} &= p_{00}[(\theta\ln(\delta) - \gamma\mu^0_c + (\theta-1)(k_{c,0} - A^0_{c,0} + k_{c,1}A^0_{c,0} + k_{c,1}A^0_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^{\$0}_{0,n-1} \\
&+ D^{\$0}_{3,n-1}\sigma^2_\pi(1-\upsilon_1) - \mu^0_\pi + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=0} + \sigma^2_c X^{s_{t+1}=0})] \\
&+ p_{01}[\theta\ln(\delta) - \gamma\mu^1_c + (\theta-1)(k_{c,0} - A^0_{c,0} + k_{c,1}A^1_{c,0} + k_{c,1}A^1_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^{\$1}_{0,n-1} \\
&+ D^{\$1}_{3,n-1}\sigma^2_\pi(1-\upsilon_1) - \mu^1_\pi + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=1} + \sigma^2_c X^{s_{t+1}=1})] && (109)\\
D^{\$1}_{0,n} &= p_{11}[\theta\ln(\delta) - \gamma\mu^1_c + (\theta-1)(k_{c,0} - A^1_{c,0} + k_{c,1}A^1_{c,0} + k_{c,1}A^1_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^{\$1}_{0,n-1} \\
&+ D^{\$1}_{3,n-1}\sigma^2_\pi(1-\upsilon_1) - \mu^1_\pi + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=1} + \sigma^2_c X^{s_{t+1}=1})] \\
&+ p_{10}[\theta\ln(\delta) - \gamma\mu^0_c + (\theta-1)(k_{c,0} - A^1_{c,0} + k_{c,1}A^0_{c,0} + k_{c,1}A^0_{c,3}\sigma^2_\pi(1-\upsilon_1)) + D^{\$0}_{0,n-1} \\
&+ D^{\$0}_{3,n-1}\sigma^2_\pi(1-\upsilon_1) - \mu^0_\pi + \frac{1}{2}(\sigma^2_\upsilon Z^{s_{t+1}=0} + \sigma^2_c X^{s_{t+1}=0})]. && (110)
\end{aligned}
$$

A.3 Innovations and Analytical Risk Premiums

The following sections present innovations and derivations of analytical risk premia for stocks, real bonds, and nominal bonds.

A.3.1 Risk Premium Formula

The conditional risk premium (given I_t) for any asset i can be derived using the Euler condition for this asset i together with the Euler equation for the 1-period risk-free rate. It is straightforward to show that the risk premium for any asset i can be expressed as:

$$\begin{aligned} E[r_{i,t+1}(s_{t+1}) - r_{f,t}|I_t] &+ \frac{1}{2}\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Var[r_{i,t+1}(s_{t+1})|I_{t+1}] \\ &= -\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Cov[m_{t+1}(s_{t+1}), r_{i,t+1}(s_{t+1})|I_{t+1}]. \end{aligned} \tag{111}$$

This equation holds for both current states $s_t = (0,1)$. Hence, given the innovations to the real pricing kernel and to the assets under considerations, we can easily derive analytical RP expressions.

A.3.2 Innovations

This section shows the innovations to stock and bond returns, nominal yields and price-dividend ratios.

The following expression represents innovations to the real pricing kernel[5], with $\lambda's$ representing the regime-dependent market prices of risk:

[5] The Innovations to the nominal pricing kernel are: $m^{\$}_{t+1}(s_{t+1}) - E[m^{\$}_{t+1}(s_{t+1})|I_{t+1}] = m_{t+1}(s_{t+1}) - E[m_{t+1}(s_{t+1})|I_{t+1}] - \sigma_{\pi,t}\eta_{\pi,t+1}$ and $m^{\$}_{t+1}(s_{t+1}) - E[m^{\$}_{t+1}(s_{t+1})|I_t] = m_{t+1}(s_{t+1}) - E[m_{t+1}(s_{t+1})|I_t] - \sigma_{\pi,t}\eta_{\pi,t+1} - \mu_\pi(s_{t+1}) + p_{s_t,0}\mu^0_\pi + p_{s_t,1}\mu^1_\pi$.

$$
\begin{aligned}
m_{t+1}(s_{t+1}) - E[m_{t+1}(s_{t+1})|I_{t+1}] &= -\lambda_{\eta_c}\sigma_c\eta_{c,t+1} - \lambda_{\varepsilon_c}(s_{t+1})\sigma_c\varepsilon_{c,t+1} - \lambda_\nu(s_{t+1})\sigma_\upsilon w_{t+1} \\
&- \lambda_{\varepsilon_\pi}(s_{t+1})\sigma_{\pi,t}\varepsilon_{\pi,t+1} \qquad (112)
\end{aligned}
$$

$$
\begin{aligned}
\lambda_{\eta_c} &= \gamma & (113) \\
\lambda_{\varepsilon_c}(s_{t+1}) &= (1-\theta)[k_{c,1}A_{c,1}(s_{t+1})\delta_1(s_{t+1}) + k_{c,1}A_{c,2}(s_{t+1})\delta_3(s_{t+1})] & (114) \\
\lambda_\nu(s_{t+1}) &= (1-\theta)k_{c,1}A_{c,3}(s_{t+1}) & (115) \\
\lambda_{\varepsilon_\pi}(s_{t+1}) &= (1-\theta)[k_{c,1}A_{c,1}(s_{t+1})\delta_2(s_{t+1}) + k_{c,1}A_{c,2}(s_{t+1})\delta_4(s_{t+1})], & (116)
\end{aligned}
$$

$$
m_{t+1}(s_{t+1}) - E[m_{t+1}(s_{t+1})|I_t] = m_{t+1}(s_{t+1}) - E[m_{t+1}(s_{t+1})|I_{t+1}] + V(s_t, s_{t+1}), \quad (117)
$$

$$
\begin{aligned}
V(s_t, s_{t+1}) &= -\gamma[\mu_c(s_{t+1}) - p_{s_t,0}\mu_c^0 - p_{s_t,1}\mu_c^1] + (\theta-1)k_{c,1}[A_{c,0}(s_{t+1}) - p_{s_t,0}A_{c,0}^0 - p_{s_t,1}A_{c,0}^1] \\
&+ (\theta-1)k_{c,1}x_{c,t}[A_{c,1}(s_{t+1})\beta_1(s_{t+1}) - p_{s_t,0}A_{c,1}^0\beta_1^0 - p_{s_t,1}A_{c,1}^1\beta_1^1] \\
&+ (\theta-1)k_{c,1}x_{\pi,t}[A_{c,1}(s_{t+1})\beta_2(s_{t+1}) - p_{s_t,0}A_{c,1}^0\beta_2^0 - p_{s_t,1}A_{c,1}^1\beta_2^1 \\
&+ A_{c,2}(s_{t+1})\beta_4(s_{t+1}) - p_{s_t,0}A_{c,2}^0\beta_4^0 - p_{s_t,1}A_{c,2}^1\beta_4^1] \\
&+ (\theta-1)k_{c,1}(\sigma_\pi^2(1-\upsilon_1) + \upsilon_1\sigma_{\pi,t}^2)[A_{c,3}(s_{t+1}) - p_{s_t,0}A_{c,3}^0 - p_{s_t,1}A_{c,3}^1]. \qquad (118)
\end{aligned}
$$

The innovations to the real and nominal return on the market portfolio:

$$
\begin{aligned}
r_{m,t+1}(s_{t+1}) - E[r_{m,t+1}(s_{t+1})|I_{t+1}] &= \sigma_c\varepsilon_{c,t+1}[k_{d,1}A_{d,1}(s_{t+1})\delta_1(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_3(s_{t+1})] \\
&+ \sigma_{\pi,t}\varepsilon_{\pi,t+1}[k_{d,1}A_{d,1}(s_{t+1})\delta_2(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_4(s_{t+1})] \\
&+ \sigma_\upsilon w_{t+1}k_{d,1}A_{d,3}(s_{t+1}) + \varphi\sigma_c\eta_{d,t+1}, \qquad (119)
\end{aligned}
$$

$$r_{m,t+1}(s_{t+1}) - E[r_{m,t+1}(s_{t+1})|I_t] \quad = \quad r_{m,t+1}(s_{t+1}) - E[r_{m,t+1}(s_{t+1})|I_{t+1}] + R(s_t, s_{t+1}), \tag{120}$$

$$\begin{aligned} R(s_t, s_{t+1}) \quad &= \quad [\mu_d(s_{t+1}) - p_{s_t,0}\mu_d^0 - p_{s_t,1}\mu_d^1] + k_{d,1}[A_{d,0}(s_{t+1}) - p_{s_t,0}A_{d,0}^0 - p_{s_t,1}A_{d,0}^1] \\ &+ \quad k_{d,1}x_{c,t}[A_{d,1}(s_{t+1})\beta_1(s_{t+1}) - p_{s_t,0}A_{d,1}^0\beta_1^0 - p_{s_t,1}A_{d,1}^1\beta_1^1] \\ &+ \quad k_{d,1}x_{\pi,t}[A_{d,1}(s_{t+1})\beta_2(s_{t+1}) - p_{s_t,0}A_{d,1}^0\beta_2^0 - p_{s_t,1}A_{d,1}^1\beta_2^1 \\ &+ \quad A_{d,2}(s_{t+1})\beta_4(s_{t+1}) - p_{s_t,0}A_{d,2}^0\beta_4^0 - p_{s_t,1}A_{d,2}^1\beta_4^1] \\ &+ \quad (\sigma_\pi^2(1-\upsilon_1) + \upsilon_1\sigma_{\pi,t}^2)[A_{d,3}(s_{t+1}) - p_{s_t,0}A_{d,3}^0 - p_{s_t,1}A_{d,3}^1], \end{aligned} \tag{121}$$

$$r^{\$}_{m,t+1}(s_{t+1}) - E[r^{\$}_{m,t+1}(s_{t+1})|I_{t+1}] = r_{m,t+1}(s_{t+1}) - E[r_{m,t+1}(s_{t+1})|I_{t+1}] + \sigma_{\pi,t}\eta_{\pi,t+1}, \tag{122}$$

$$r^{\$}_{m,t+1}(s_{t+1}) - E[r^{\$}_{m,t+1}(s_{t+1})|I_t] \quad = \quad r^{\$}_{m,t+1}(s_{t+1}) - E[r^{\$}_{m,t+1}(s_{t+1})|I_{t+1}] + R^{\$}(s_t, s_{t+1}), \tag{123}$$

$$R^{\$}(s_t, s_{t+1}) \quad = \quad R(s_t, s_{t+1}) + \mu_\pi(s_{t+1}) + p_{s_t,0}\mu_\pi^0 + p_{s_t,1}\mu_\pi^1. \tag{124}$$

The return from holding a n-period real bond for one period is $h_{t+1,n}(s_{t+1}) = q_{t+1,n-1}(s_{t+1}) - q_{t,n}(s_t)$. The innovation to this return is [6]:

[6] To get the innovation to the return of a nominal bond, just replace the D-coefficients by $D^{\$}$-coefficients.

$$
\begin{aligned}
h_{t+1,n}(s_{t+1}) - E[h_{t+1,n}(s_{t+1})|I_{t+1}] &= \sigma_c \varepsilon_{c,t+1}[D_{1,n-1}(s_{t+1})\delta_1(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_3(s_{t+1})] \\
&+ \sigma_{\pi,t}\varepsilon_{\pi,t+1}[D_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_4(s_{t+1})] \\
&+ \sigma_\upsilon w_{t+1} D_{3,n-1}(s_{t+1}), \qquad (125)
\end{aligned}
$$

$$
h_{t+1,n}(s_{t+1}) - E[h_{t+1,n}(s_{t+1})|I_t] = h_{t+1,n}(s_{t+1}) - E[h_{t+1,n}(s_{t+1})|I_{t+1}] + H(s_t, s_{t+1}), \qquad (126)
$$

$$
\begin{aligned}
H(s_t, s_{t+1}) &= [D_{0,n-1}(s_{t+1}) - p_{s_t,0}D^0_{0,n-1} - p_{s_t,1}D^1_{0,n-1}] \\
&+ x_{c,t}[D_{1,n-1}(s_{t+1})\beta_1(s_{t+1}) - p_{s_t,0}D^0_{1,n-1}\beta^0_1 - p_{s_t,1}D^1_{1,n-1}\beta^1_1] \\
&+ x_{\pi,t}[D_{1,n-1}(s_{t+1})\beta_2(s_{t+1}) - p_{s_t,0}D^0_{1,n-1}\beta^0_2 - p_{s_t,1}D^1_{1,n-1}\beta^1_2 \\
&+ D_{2,n-1}(s_{t+1})\beta_4(s_{t+1}) - p_{s_t,0}D^0_{2,n-1}\beta^0_4 - p_{s_t,1}D^1_{2,n-1}\beta^1_4] \\
&+ (\sigma^2_\pi(1-\upsilon_1) + \upsilon_1\sigma^2_{\pi,t})[D_{3,n-1}(s_{t+1}) - p_{s_t,0}D^0_{3,n-1} - p_{s_t,1}D^1_{3,n-1}]. \qquad (127)
\end{aligned}
$$

Innovations to real yields:

$$
\begin{aligned}
y_{t+1,n}(s_{t+1}) - E[y_{t+1,n}(s_{t+1})|I_{t+1}] = -\frac{1}{n}\Bigg[&\sigma_c \varepsilon_{c,t+1}[D_{1,n-1}(s_{t+1})\delta_1(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_3(s_{t+1})] \\
&+ \sigma_{\pi,t}\varepsilon_{\pi,t+1}[D_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_4(s_{t+1})] \\
&+ \sigma_\upsilon w_{t+1} D_{3,n-1}(s_{t+1})\Bigg], \qquad (128)
\end{aligned}
$$

$$
y_{t+1,n}(s_{t+1}) - E[y_{t+1,n}(s_{t+1})|I_t] = y_{t+1,n}(s_{t+1}) - E[y_{t+1,n}(s_{t+1})|I_{t+1}] + Q(s_t, s_{t+1}), \qquad (129)
$$

$$
\begin{aligned}
Q(s_t, s_{t+1}) &= -\frac{1}{n}\Bigg[[D_{0,n}(s_{t+1}) - p_{s_t,0}D^0_{0,n} - p_{s_t,1}D^1_{0,n}] \\
&+ x_{c,t}[D_{1,n}(s_{t+1})\beta_1(s_{t+1}) - p_{s_t,0}D^0_{1,n}\beta^0_1 - p_{s_t,1}D^1_{1,n}\beta^1_1] \\
&+ x_{\pi,t}[D_{1,n}(s_{t+1})\beta_2(s_{t+1}) - p_{s_t,0}D^0_{1,n}\beta^0_2 - p_{s_t,1}D^1_{1,n}\beta^1_2 \\
&+ D_{2,n}(s_{t+1})\beta_4(s_{t+1}) - p_{s_t,0}D^0_{2,n}\beta^0_4 - p_{s_t,1}D^1_{2,n}\beta^1_4] \\
&+ (\sigma^2_\pi(1-\upsilon_1) + \upsilon_1\sigma^2_{\pi,t})[D_{3,n}(s_{t+1}) - p_{s_t,0}D^0_{3,n} - p_{s_t,1}D^1_{3,n}]\Bigg]. \qquad (130)
\end{aligned}
$$

Innovations to nominal yields:

$$
\begin{aligned}
y^\$_{t+1,n}(s_{t+1}) - E[y^\$_{t+1,n}(s_{t+1})|I_{t+1}] = -\frac{1}{n}\Bigg[&\sigma_c\varepsilon_{c,t+1}[D^\$_{1,n-1}(s_{t+1})\delta_1(s_{t+1}) + D^\$_{2,n-1}(s_{t+1})\delta_3(s_{t+1})] \\
&+ \sigma_{\pi,t}\varepsilon_{\pi,t+1}[D^\$_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) + D^\$_{2,n-1}(s_{t+1})\delta_4(s_{t+1})] \\
&+ \sigma_\upsilon w_{t+1}D^\$_{3,n-1}(s_{t+1})\Bigg], \qquad (131)
\end{aligned}
$$

$$
y^\$_{t+1,n}(s_{t+1}) - E[y^\$_{t+1,n}(s_{t+1})|I_t] = y^\$_{t+1,n}(s_{t+1}) - E[y^\$_{t+1,n}(s_{t+1})|I_{t+1}] + Q^\$(s_t, s_{t+1}), \qquad (132)
$$

$$
\begin{aligned}
Q^\$(s_t, s_{t+1}) &= -\frac{1}{n}\Bigg[[D^\$_{0,n}(s_{t+1}) - p_{s_t,0}D^{\$,0}_{0,n} - p_{s_t,1}D^{\$,1}_{0,n}] \\
&+ x_{c,t}[D^\$_{1,n}(s_{t+1})\beta_1(s_{t+1}) - p_{s_t,0}D^{\$,0}_{1,n}\beta^0_1 - p_{s_t,1}D^{\$,1}_{1,n}\beta^1_1] \\
&+ x_{\pi,t}[D^\$_{1,n}(s_{t+1})\beta_2(s_{t+1}) - p_{s_t,0}D^{\$,0}_{1,n}\beta^0_2 - p_{s_t,1}D^{\$,1}_{1,n}\beta^1_2 \\
&+ D^\$_{2,n}(s_{t+1})\beta_4(s_{t+1}) - p_{s_t,0}D^{\$,0}_{2,n}\beta^0_4 - p_{s_t,1}D^{\$,1}_{2,n}\beta^1_4] \\
&+ (\sigma^2_\pi(1-\upsilon_1) + \upsilon_1\sigma^2_{\pi,t})[D^\$_{3,n}(s_{t+1}) - p_{s_t,0}D^{\$,0}_{3,n} - p_{s_t,1}D^{\$,1}_{3,n}]\Bigg]. \qquad (133)
\end{aligned}
$$

And finally the innovations to the price-dividend ratio:

$$
\begin{aligned}
pd_{t+1}(s_{t+1}) - E[pd_{t+1}(s_{t+1})|I_{t+1}] &= \sigma_c \varepsilon_{c,t+1}[A_{d,1}(s_{t+1})\delta_1(s_{t+1}) + A_{d,2}(s_{t+1})\delta_3(s_{t+1})] \\
&+ \sigma_{\pi,t}\varepsilon_{\pi,t+1}[A_{d,1}(s_{t+1})\delta_2(s_{t+1}) + A_{d,2}(s_{t+1})\delta_4(s_{t+1})] \\
&+ \sigma_\upsilon w_{t+1} A_{d,3}(s_{t+1}), \qquad (134)
\end{aligned}
$$

$$
pd_{t+1}(s_{t+1}) - E[pd_{t+1}(s_{t+1})|I_t] = pd_{t+1}(s_{t+1}) - E[pd_{t+1}(s_{t+1})|I_{t+1}] + S(s_t, s_{t+1}), \qquad (135)
$$

$$
\begin{aligned}
S(s_t, s_{t+1}) &= [A_{d,0}(s_{t+1}) - p_{s_t,0}A^0_{d,0} - p_{s_t,1}A^1_{d,0}] \\
&+ x_{c,t}[A_{d,1}(s_{t+1})\beta_1(s_{t+1}) - p_{s_t,0}A^0_{d,1}\beta^0_1 - p_{s_t,1}A^1_{d,1}\beta^1_1] \\
&+ x_{\pi,t}[A_{d,1}(s_{t+1})\beta_2(s_{t+1}) - p_{s_t,0}A^0_{d,1}\beta^0_2 - p_{s_t,1}A^1_{d,1}\beta^1_2 \\
&+ A_{d,2}(s_{t+1})\beta_4(s_{t+1}) - p_{s_t,0}A^0_{d,2}\beta^0_4 - p_{s_t,1}A^1_{d,2}\beta^1_4] \\
&+ (\sigma^2_\pi(1-\upsilon_1) + \upsilon_1\sigma^2_{\pi,t})[A_{d,3}(s_{t+1}) - p_{s_t,0}A^0_{d,3} - p_{s_t,1}A^1_{d,3}]. \qquad (136)
\end{aligned}
$$

A.3.3 Risk Premiums

Using the formula from A.3.1, the risk premium for the market portfolio can be expressed as:

$$
\begin{aligned}
E[r_{m,t+1}(s_{t+1}) - r_{f,t}|I_t] &+ \frac{1}{2}\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Var[r_{m,t+1}(s_{t+1})|I_{t+1}] \qquad (137) \\
&= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}}[A(s_{t+1}) + B(s_{t+1})\sigma^2_{\pi,t}],
\end{aligned}
$$

$$A(s_{t+1}) = \sigma_c^2[k_{d,1}A_{d,1}(s_{t+1})\delta_1(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_3(s_{t+1})]\lambda_{\varepsilon_c}(s_{t+1}) \tag{138}$$

$$+ \sigma_v^2 k_{d,1}A_{d,3}(s_{t+1})\lambda_v(s_{t+1}),$$

$$B(s_{t+1}) = [k_{d,1}A_{d,1}(s_{t+1})\delta_2(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_4(s_{t+1})]\lambda_{\varepsilon_\pi}(s_{t+1}). \tag{139}$$

The risk premium for real bonds is:

$$E[h_{t+1,n}(s_{t+1}) - r_{f,t}|I_t] + \frac{1}{2}\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Var[h_{t+1,n}(s_{t+1})|I_{t+1}] \tag{140}$$

$$= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}}[A(s_{t+1}) + B(s_{t+1})\sigma_{\pi,t}^2],$$

$$A(s_{t+1}) = \sigma_c^2[D_{1,n-1}(s_{t+1})\delta_1(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_3(s_{t+1})]\lambda_{\varepsilon_c}(s_{t+1}) \tag{141}$$

$$+ \sigma_v^2 D_{3,n-1}(s_{t+1})\lambda_v(s_{t+1}),$$

$$B(s_{t+1}) = [D_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) + D_{2,n-1}(s_{t+1})\delta_4(s_{t+1})]\lambda_{\varepsilon_\pi}(s_{t+1}). \tag{142}$$

The risk premium for nominal bonds:

$$E[h^{\$}_{t+1,n}(s_{t+1}) - r^{\$}_{f,t}|I_t] + \frac{1}{2}\sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}} Var[h^{\$}_{t+1,n}(s_{t+1})|I_{t+1}] \tag{143}$$

$$= \sum_{s_{t+1}=0,1} p_{s_t,s_{t+1}}[A^{\$}(s_{t+1}) + B^{\$}(s_{t+1})\sigma_{\pi,t}^2],$$

$$A^{\$}(s_{t+1}) = \sigma_c^2[D^{\$}_{1,n-1}(s_{t+1})\delta_1(s_{t+1}) + D^{\$}_{2,n-1}(s_{t+1})\delta_3(s_{t+1})]\lambda_{\varepsilon_c}(s_{t+1}) \tag{144}$$

$$+ \sigma_v^2 D^{\$}_{3,n-1}(s_{t+1})\lambda_v(s_{t+1}),$$

$$B^{\$}(s_{t+1}) = [D^{\$}_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) + D^{\$}_{2,n-1}(s_{t+1})\delta_4(s_{t+1})]\lambda_{\varepsilon_\pi}(s_{t+1}). \tag{145}$$

A.4 Analytical Asset Correlations

A.4.1 Stock and Bond Returns

The conditional covariance between nominal stock and bond returns can be expressed as follows:

$$Cov[r^{\$}_{m,t+1}(s_{t+1}), h^{\$}_{t+1,n}(s_{t+1})|I_t] = \tag{146}$$

$$E\left[E[(r^{\$}_{m,t+1}(s_{t+1}) - E[r^{\$}_{m,t+1}(s_{t+1})|I_t])(h^{\$}_{t+1,n}(s_{t+1}) - E[h^{\$}_{t+1,n}(s_{t+1})|I_t])|I_{t+1}]|I_t\right].$$

Using the innovations derived in section A.3.2, the inner part of the above expression can be written as:

$$\begin{aligned} E[(r^{\$}_{m,t+1}(s_{t+1}) - E[r^{\$}_{m,t+1}(s_{t+1})|I_t])(h^{\$}_{t+1,n}(s_{t+1}) - E[h^{\$}_{t+1,n}(s_{t+1})|I_t])|I_{t+1}] \\ = L(s_{t+1}) + R^{\$}(s_t, s_{t+1})H^{\$}(s_t, s_{t+1}), \end{aligned}$$

with $R^{\$}(s_t, s_{t+1})$ from Equation (124) and $H^{\$}(s_t, s_{t+1})$ from Equation (127), with D's replaced by $D^{\$}$'s and with

$$
\begin{aligned}
L(s_{t+1}) &= \sigma_c^2[k_{d,1}A_{d,1}(s_{t+1})\delta_1(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_3(s_{t+1})][D^{\$}_{1,n-1}(s_{t+1})\delta_1(s_{t+1}) \\
&+ D^{\$}_{2,n-1}(s_{t+1})\delta_3(s_{t+1})] \\
&+ \sigma_{\pi,t}^2[k_{d,1}A_{d,1}(s_{t+1})\delta_2(s_{t+1}) + k_{d,1}A_{d,2}(s_{t+1})\delta_4(s_{t+1})][D^{\$}_{1,n-1}(s_{t+1})\delta_2(s_{t+1}) \\
&+ D^{\$}_{2,n-1}(s_{t+1})\delta_4(s_{t+1})] \\
&+ \sigma_v^2 k_{d,1}A_{d,3}(s_{t+1})D^{\$}_{3,n-1}(s_{t+1}). \qquad (147)
\end{aligned}
$$

Hence, the conditional covariance betweens stock and bond returns is:

$$
\begin{aligned}
Cov[r^{\$}_{m,t+1}(s_{t+1}), h^{\$}_{t+1,n}(s_{t+1})|I_t] &= p_{s_t,0}[R^{\$}(s_t,0)H^{\$}(s_t,0) + L(0)] \\
&+ p_{s_t,1}[R^{\$}(s_t,1)H^{\$}(s_t,1) + L(1)].
\end{aligned} \qquad (148)
$$

Equivalently the conditional covariance betweens stock and bond returns can also be written as:

$$
Cov[r^{\$}_{m,t+1}(s_{t+1}), h^{\$}_{t+1,n}(s_{t+1})|I_t] = M_t + A + B\sigma^2_{\pi,t}, \qquad (149)
$$

$$
\begin{aligned}
B &= p_{s_t,0}[k_{d,1}A^0_{d,1}\delta^0_2 + k_{d,1}A^0_{d,2}\delta^0_4][D^{\$,0}_{1,n-1}\delta^0_2 + D^{\$,0}_{2,n-1}\delta^0_4] \\
&+ p_{s_t,1}[k_{d,1}A^1_{d,1}\delta^1_2 + k_{d,1}A^1_{d,2}\delta^1_4][D^{\$,1}_{1,n-1}\delta^1_2 + D^{\$,1}_{2,n-1}\delta^1_4], \qquad (150)
\end{aligned}
$$

$$
\begin{aligned}
A &= p_{s_t,0}\Bigg[\sigma_c^2[k_{d,1}A^0_{d,1}\delta^0_1 + k_{d,1}A^0_{d,2}\delta^0_3][D^{\$,0}_{1,n-1}\delta^0_1 + D^{\$,0}_{2,n-1}\delta^0_3] \\
&+ \sigma_\upsilon^2 k_{d,1}A^0_{d,3}D^{\$,0}_{3,n-1}\Bigg] \\
&+ p_{s_t,1}\Bigg[\sigma_c^2[k_{d,1}A^1_{d,1}\delta^1_1 + k_{d,1}A^1_{d,2}\delta^1_3][D^{\$,1}_{1,n-1}\delta^1_1 + D^{\$,1}_{2,n-1}\delta^1_3] \\
&+ \sigma_\upsilon^2 k_{d,1}A^1_{d,3}D^{\$,1}_{3,n-1}\Bigg],
\end{aligned} \tag{151}
$$

$$
M_t = p_{s_t,0}[R^{\$}(s_t,0)H^{\$}(s_t,0)] + p_{s_t,1}[R^{\$}(s_t,1)H^{\$}(s_t,1)]. \tag{152}
$$

A.4.2 Price-Dividend Ratio and Nominal Yields

Using the same approach as in section A.4.1, it is straightforward to show that the conditional covariance between price-dividend ratios and nominal yields can be stated as:

$$
Cov[pd_{t+1}(s_{t+1}), y^{\$}_{t+1,n}(s_{t+1})|I_t] = M_t + A + B\sigma^2_{\pi,t}, \tag{153}
$$

$$
\begin{aligned}
B &= -\frac{1}{n}\Bigg[p_{s_t,0}[A^0_{d,1}\delta^0_2 + A^0_{d,2}\delta^0_4][D^{\$,0}_{1,n-1}\delta^0_2 + D^{\$,0}_{2,n-1}\delta^0_4] \\
&+ p_{s_t,1}[A^1_{d,1}\delta^1_2 + A^1_{d,2}\delta^1_4][D^{\$,1}_{1,n-1}\delta^1_2 + D^{\$,1}_{2,n-1}\delta^1_4]\Bigg],
\end{aligned} \tag{154}
$$

$$
\begin{aligned}
A &= -\frac{1}{n}\Bigg[p_{s_t,0}\Bigg[\sigma_c^2[A^0_{d,1}\delta^0_1 + A^0_{d,2}\delta^0_3][D^{\$,0}_{1,n-1}\delta^0_1 + D^{\$,0}_{2,n-1}\delta^0_3] \\
&+ \sigma_\upsilon^2 A^0_{d,3}D^{\$,0}_{3,n-1}\Bigg] \\
&+ p_{s_t,1}\Bigg[\sigma_c^2[A^1_{d,1}\delta^1_1 + A^1_{d,2}\delta^1_3][D^{\$,1}_{1,n-1}\delta^1_1 + D^{\$,1}_{2,n-1}\delta^1_3] \\
&+ \sigma_\upsilon^2 A^1_{d,3}D^{\$,1}_{3,n-1}\Bigg]\Bigg],
\end{aligned} \tag{155}
$$

$$
M_t = -\frac{1}{n}\Bigg[p_{s_t,0}[S(s_t,0)Q^{\$}(s_t,0)] + p_{s_t,1}[S(s_t,1)Q^{\$}(s_t,1)]\Bigg], \tag{156}
$$

with $S(s_t, s_{t+1})$ given in Equation (136) and $Q^{\$}(s_t, s_{t+1})$ given in Equation (133).

A.5 Yield Curve Slope Components

As above, let $y_{t,n}(s_t) = -\frac{1}{n} q_{t,n}(s_t)$ denote the n-period log yield with $q_{t,n}$ being the log price at time t of a real bond with maturity of n periods (t and n are both expressed in quarters).

A.5.1 Expectations Hypothesis

According to the expectations hypothesis, the long-term yield can be written as the average of the expected future short term rates plus a risk premium part that we label term premium:

$$y_{t,n}(s_t) = \frac{1}{n} E[y_{t,1}(s_t) + y_{t+1,1}(s_{t+1}) + ... + y_{t+n-1,1}(s_{t+n-1})|I_t] + RPT_{t,n}(s_t). \tag{157}$$

It follows that the slope of the yield curve can be written as the sum of two components, namely the "expectations-part" plus the "term premium part":

$$\begin{aligned} y_{t,n}(s_t) - y_{t,1}(s_t) &= \frac{1}{n} y_{t,1}(s_t) - y_{t,1}(s_t) + \frac{1}{n} E[y_{t+1,1}(s_{t+1}) + ... + y_{t+n-1,1}(s_{t+n-1})|I_t] \\ &+ RPT_{t,n}(s_t). \end{aligned} \tag{158}$$

In the single-regime case taking the unconditional expectation of (158) and using the law of iterated expectations implies that the expected yield curve slope is equal to the unconditional expectation of the term premium $RPT_{t,n}$. This is however not the case in a setup featuring multiple regimes. When taking the unconditional expectation of the yield curve slope conditional on a given regime $s_t = s$, the mean yield curve slope also depends on expectations of future short rates.

For the single-regime case and $n = 2$ we have $y_{t,2} - y_{t,1} = -\frac{1}{2}y_{t,1} + \frac{1}{2}E[y_{t+1,1}|I_t] + RPT_{t,2}$. Taking the unconditional expectation gives us:

$$E[y_{t,2} - y_{t,1}] = \underbrace{-\frac{1}{2}E[y_{t,1}] + \frac{1}{2}E\{E[y_{t+1,1}|I_t]\}}_{=0} + E[RPT_{t,2}], \text{ and hence} \tag{159}$$

$$E[y_{t,2} - y_{t,1}] = E[RPT_{t,2}]. \tag{160}$$

For the regime-switching case with 2 regimes and $n = 2$ on the other hand, we have $y_{t,2}(s_t) - y_{t,1}(s_t) = -\frac{1}{2}y_{t,1}(s_t) + \frac{1}{2}E[y_{t+1,1}(s_{t+1})|I_t] + RPT_{t,2}(s_t)$. Now taking expectations of both sides of this equation conditional on regime $s_t = s$ (unconditional expectation in regime s) results in:

$$\begin{aligned} E[y_{t,2}(s_t) - y_{t,1}(s_t)|s_t = s] = & -\frac{1}{2}E[y_{t,1}(s_t)|s_t = s] + \frac{1}{2}E\{E[y_{t+1,1}(s_{t+1})|I_t]|s_t = s\} \\ & + E[RPT_{t,2}(s_t)|s_t = s]. \end{aligned} \tag{161}$$

The term $E\{E[y_{t+1,1}(s_{t+1})|I_t]|s_t = s\}$ is equivalent to:

$$\begin{aligned} E\{E[y_{t+1,1}(s_{t+1})|I_t]|s_t = s\} &= p_{s,0}E\{E[y_{t+1,1}(s_{t+1})|I_t, s_{t+1} = 0]|s_t = s\} \\ &+ p_{s,1}E\{E[y_{t+1,1}(s_{t+1})|I_t, s_{t+1} = 1]|s_t = s\} \\ &= p_{s,0}E[y_{t+1,1}(s_{t+1})|s_t = s, s_{t+1} = 0] \\ &+ p_{s,1}E[y_{t+1,1}(s_{t+1})|s_t = s, s_{t+1} = 1]. \end{aligned}$$

As a result the expected 2-period slope conditional on regime $s_t = s$ can be stated as:

$$
\begin{aligned}
E[y_{t,2}(s_t) - y_{t,1}(s_t)|s_t = s] = & - \frac{1}{2}E[y_{t,1}(s_t)|s_t = s] \\
& + \frac{1}{2}\{p_{s,0}E[y_{t+1,1}(s_{t+1})|s_t = s, s_{t+1} = 0] \\
& + p_{s,1}E[y_{t+1,1}(s_{t+1})|s_t = s, s_{t+1} = 1]\} \\
& + E[RPT_{t,2}(s_t)|s_t = s]. \qquad (162)
\end{aligned}
$$

Within our model $E\{E[y_{t+1,1}(s_{t+1})|I_t]|s_t = s\}$ can be written as:

$$
E\{E[y_{t+1,1}(s_{t+1})|I_t]|s_t = s\} = -[p_{s,0}\{D^0_{0,1} + D^0_{3,1}\sigma^2_\pi\} + p_{s,1}\{D^1_{0,1} + D^1_{3,1}\sigma^2_\pi\}], \qquad (163)
$$

and the expected 2-period slope conditional on regime $s_t = s$ is:

$$
\begin{aligned}
E[y_{t,2}(s_t) - y_{t,1}(s_t)|s_t = s] = & \frac{1}{2}[D^s_{0,1} + D^s_{3,1}\sigma^2_\pi] \\
& - \frac{1}{2}\{p_{s,0}\{D^0_{0,1} + D^0_{3,1}\sigma^2_\pi\} + p_{s,1}\{D^1_{0,1} + D^1_{3,1}\sigma^2_\pi\}] \\
& + E[RPT_{t,2}(s_t)|s_t = s]. \qquad (164)
\end{aligned}
$$

Taking the unconditional expectation of (158) again implies that the expected yield curve slope equals the unconditional[7] expectation of the term premium $RPT_{t,n}$:

$$
\begin{aligned}
E[y_{t,2}(s_t) - y_{t,1}(s_t)] &= p_0E[y_{t,2}(s_t) - y_{t,1}(s_t)|s = 0] + p_1E[y_{t,2}(s_t) - y_{t,1}(s_t)|s = 1] \\
&= p_0E[RPT_{t,2}(s_t)|s = 0] + p_1E[RPT_{t,2}(s_t)|s = 1] \\
&= E[RPT_{t,2}(s_t)]. \qquad (165)
\end{aligned}
$$

[7] Considering two states, i and j, the unconditional probability of being in state j is computed as $p_j = \frac{1-p_{i,i}}{2-p_{j,j}-p_{i,i}}$.

A.5.2 Slope Components - Analytical Expressions

In a first step we write down our system and bond prices in vector notation:

$$
\begin{aligned}
X_{t+1} &= \mu + \beta(s_{t+1})X_t + \delta(s_{t+1})\varepsilon_{t+1} && (166)\\
q_{t,n}(s_t) &= D_{0,n}(s_t) + B_n(s_t)X_t, && (167)
\end{aligned}
$$

with

$$
\begin{aligned}
X_{t+1} &= \begin{bmatrix} x_{c,t+1} \\ x_{\pi,t+1} \\ \sigma^2_{\pi,t+1} \end{bmatrix}, \; \mu = \begin{bmatrix} 0 \\ 0 \\ \sigma^2_\pi(1-\upsilon_1) \end{bmatrix}, \; \varepsilon_{t+1} = \begin{bmatrix} \varepsilon_{c,t+1} \\ \varepsilon_{\pi,t+1} \\ w_{t+1} \end{bmatrix}, \\
\beta(s_{t+1}) &= \begin{bmatrix} \beta_1(s_{t+1}) & \beta_2(s_{t+1}) & 0 \\ 0 & \beta_4(s_{t+1}) & 0 \\ 0 & 0 & \upsilon_1 \end{bmatrix}, \\
\delta(s_{t+1}) &= \begin{bmatrix} \delta_1(s_{t+1})\sigma_c & \delta_2(s_{t+1})\sigma_{\pi,t} & 0 \\ \delta_3(s_{t+1})\sigma_c & \delta_4(s_{t+1})\sigma_{\pi,t} & 0 \\ 0 & 0 & \sigma_\upsilon \end{bmatrix} \text{ and } B_n(s_t) = \begin{bmatrix} D_{1,n}(s_t) \\ D_{2,n}(s_t) \\ D_{3,n}(s_t) \end{bmatrix}'.
\end{aligned}
$$

In order to write out the "expectations-part", we need analytical expressions for the expected future short rates $E[y_{t+n,1}(s_{t+n}) \mid I_t]$. Within the model, today's expectations of future short rates can be written as:

$$
\underbrace{E[y_{t+n,1}(s_{t+n}) \mid I_t]}_{(2\times1)} = E[-D_{0,1}(s_{t+n}) - B_1(s_{t+n})X_{t+n} \mid I_t] \qquad (168)
$$

$$= (-[D_{0,1}(0)\ D_{0,1}(1)]\ P^n)' - \begin{bmatrix} \mathbf{1}_{(1\times 2)}\ B\ [\Pi^n \begin{bmatrix} 1 \\ 0 \end{bmatrix} \bigotimes X_t + \sum_{i=0}^{n-1} \Pi^i\ L\ \{(P^{n-(i+1)} \begin{bmatrix} 1 \\ 0 \end{bmatrix}) \bigotimes \mu\}] \\ \mathbf{1}_{(1\times 2)}\ B\ [\Pi^n \begin{bmatrix} 0 \\ 1 \end{bmatrix} \bigotimes X_t + \sum_{i=0}^{n-1} \Pi^i\ L\ \{(P^{n-(i+1)} \begin{bmatrix} 0 \\ 1 \end{bmatrix}) \bigotimes \mu\}] \end{bmatrix} \tag{169}$$

with

$$\underbrace{P}_{(2\times 2)} = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix}, \underbrace{B}_{(2\times 6)} = \begin{bmatrix} D_{1,1}(0) & D_{2,1}(0) & D_{3,1}(0) & 0 & 0 & 0 \\ 0 & 0 & 0 & D_{1,1}(1) & D_{2,1}(1) & D_{3,1}(1) \end{bmatrix},$$

$$\underbrace{\Pi}_{(6\times 6)} = \begin{bmatrix} p_{00}\beta(0) & p_{10}\beta(0) \\ p_{01}\beta(1) & p_{11}\beta(1) \end{bmatrix}, \underbrace{L}_{(6\times 6)} = \begin{bmatrix} p_{00}I_3 & p_{10}I_3 \\ p_{01}I_3 & p_{11}I_3 \end{bmatrix} \text{ and } I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{170}$$

$E[y_{t+n,1}(s_{t+n}) \mid I_t]$ is a (2×1)-vector with the first row containing the expected future short rate given we are in regime $s_t = 0$ today and the second row giving the expected future short rate given we are in regime $s_t = 1$ today.

Note that the slope of the yield curve, $y_{t,n}(s_t) - y_{t,1}(s_t)$, can be expressed as follows:

$$y_{t,n}(s_t) - y_{t,1}(s_t) = -\frac{1}{n} D_{0,n}(s_t) + D_{0,1}(s_t) + \{B_1(s_t) - \frac{1}{n} B_n(s_t)\} X_t. \tag{171}$$

The term premium $RPT_{t,n}$ in the model can therefore be calculated as the difference between (171) and the "expectations-part" from equation (158) using the expressions for expected short rates given by (169). These derivations also hold for nominal bonds by replacing the D-coefficients by $D^{\$}$-coefficients.

B Appendix II: Additional Empirical Results

B.1 Regressions using conditional variance of inflation as measure for inflation risk

Table I. Regressing Price-Dividend Ratios onto Inflation and Inflation Risk This table presents results from regressing log price-dividend ratios onto expected inflation (β_π) and inflation risk ($\beta_{\sigma_\pi^2}$): $pd_t = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma_\pi^2}\sigma_{\pi,t}^2 + \epsilon_t$. Inflation risk is measured as the conditional variance of inflation and is estimated from an AR(1)-GARCH(1,1) on expected inflation. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1965:1-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma_\pi^2}$	t-stat	R^2
Full sample	–0.38	–5.18	–1.26	–1.99	0.31
Countercyclical state	–0.21	–3.73	–6.99	–5.33	0.62
Procyclical state	0.16	1.83	–1.17	–4.45	0.54

Table II. Regressing Nominal Yields onto Inflation and Inflation Risk This table presents results from regressing 5-year nominal interest rates onto expected inflation (β_π) and inflation risk ($\beta_{\sigma_\pi^2}$): $y_{t,5y}^{\$} = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma_\pi^2}\sigma_{\pi,t}^2 + \epsilon_t$. Inflation risk is measured as the conditional variance of inflation and is estimated from an AR(1)-GARCH(1,1) on expected inflation. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1965:1-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma_\pi^2}$	t-stat	R^2
Full sample	2.67	5.34	–5.10	–1.22	0.26
Countercyclical state	0.63	1.22	55.76	4.03	0.48
Procyclical state	0.70	2.80	– 6.44	–2.85	0.38

Table III. Predicting Covariance of Stock and Bond Returns This table presents results from predicting quarterly covariances between returns on US stocks and Treasury bonds using inflation risk: $\sigma(r_{stock,t+1}, r_{bond,t+1}) = \alpha + \beta_{\sigma_\pi^2}\sigma_{\pi,t}^2 + \epsilon_t$. Dependent variable is the realized quarterly covariance between stock and bond returns computed using daily returns. The independent variable consists of inflation volatility estimated from an AR(1)-GARCH(1,1) on expected inflation. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1965:1-1999:4 and the procyclical state to 2000:1-2011:4.

	Data		
	$\beta_{\sigma_\pi^2}$	t-stat	R^2
Full sample	–0.53	–3.26	0.04
Countercyclical state	1.06	2.81	0.12
Procyclical state	–0.20	–0.96	0.00

B.2 Regressions using dispersion of CPI forecasts as measure for inflation risk

Table IV. Regressing Price-Dividend Ratios onto Inflation and Inflation Risk This table presents results from regressing log price-dividend ratios onto expected inflation (β_π) and inflation risk ($\beta_{\sigma_\pi^2}$): $pd_t = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma_\pi^2}\sigma_{\pi,t}^2 + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of CPI inflation, taken from Survey of Professional Forecasters. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma_\pi^2}$	t-stat	R^2
Full sample	–0.13	–0.97	–26.29	–4.55	0.31
Countercyclical state	–0.49	–3.59	–14.79	–3.15	0.40
Procyclical state	0.12	1.85	–45.26	–4.19	0.51

Table V. Regressing Nominal Yields onto Inflation and Inflation Risk This table presents results from regressing 5-year nominal interest rates onto expected inflation (β_π) and inflation risk ($\beta_{\sigma^2_\pi}$): $y^{\$}_{t,5y} = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi}\sigma^2_{\pi,t} + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of CPI inflation, taken from Survey of Professional Forecasters. Inflation expectations are created by projecting quarterly demeaned inflation onto lagged growth, inflation, and yield spread. All regressions are run contemporaneously. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma^2_\pi}$	t-stat	R^2
Full sample	3.39	4.96	148.95	4.11	0.33
Countercyclical state	3.70	3.88	108.32	3.27	0.45
Procyclical state	0.74	1.89	–156.12	–2.46	0.20

Table VI. Predicting Covariance of Stock and Bond Returns This table presents results from predicting quarterly covariances between returns on US stocks and Treasury bonds using inflation risk: $\sigma(r_{stock,t+1}, r_{bond,t+1}) = \alpha + \beta_{\sigma^2_\pi}\sigma^2_{\pi,t} + \epsilon_t$. Dependent variable is the realized quarterly covariance between stock and bond returns computed using daily returns. Independent variable is the cross-sectional variance of individual forecasters of CPI inflation, taken from Survey of Professional Forecasters. Standard errors are computed using Newey and West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data		
	$\beta_{\sigma^2_\pi}$	t-stat	R^2
Full sample	4.52	1.93	0.02
Countercyclical state	3.80	4.04	0.18
Procyclical state	–29.99	–2.34	0.13

B.3 Regressions using long-run inflation as measure of expected inflation

Table VII. Regressing Price-Dividend Ratios onto Inflation and Inflation Risk This table presents results from regressing log price-dividend ratios onto expected inflation (β_π) and inflation risk ($\beta_{\sigma^2_\pi}$): $pd_t = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi} \sigma^2_{\pi,t} + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Inflation expectations are measured as the long-run mean of inflation: $\frac{\sum_{i=0}^{t-1} v^i \pi_{t-i}}{\sum_{i=0}^{t-1} v^i}$ where v is set equal to 0.98 and where we consider a backward looking period of 40 quarters. All regressions are run contemporaneously. Standard errors are computed using Newey-West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma^2_\pi}$	t-stat	R^2
Full sample	–0.47	–6.59	–31.26	–4.59	0.66
Countercyclical state	–0.37	–4.45	–27.27	–4.40	0.56
Procyclical state	–1.35	–1.63	–82.97	–3.88	0.56

Table VIII. Regressing Nominal Yields onto Inflation and Inflation Risk This table presents results from regressing 5-year nominal interest rates onto expected inflation (β_π) and inflation risk ($\beta_{\sigma^2_\pi}$): $y^{\$}_{t,5y} = \alpha + \beta_\pi x_{\pi,t} + \beta_{\sigma^2_\pi} \sigma^2_{\pi,t} + \epsilon_t$. Inflation risk is measured as the cross-sectional variance of individual forecasters of the GDP price deflator (PGDP), taken from Survey of Professional Forecasters. Inflation expectations are measured as the long-run mean of inflation: $\frac{\sum_{i=0}^{t-1} v^i \pi_{t-i}}{\sum_{i=0}^{t-1} v^i}$ where v is set equal to 0.98 and where we consider a backward looking period of 40 quarters. All regressions are run contemporaneously. Standard errors are computed using Newey-West (1987) with 4 lags. The countercyclical state refers to 1968:4-1999:4 and the procyclical state to 2000:1-2011:4.

	Data				
	β_π	t-stat	$\beta_{\sigma^2_\pi}$	t-stat	R^2
Full sample	4.97	7.33	64.34	1.42	0.69
Countercyclical state	3.76	5.42	82.85	1.89	0.64
Procyclical state	–0.64	–0.10	–437.56	–2.50	0.25

Time-Varying Inflation Risk and the Cross-Section of Stock Returns

Dominic Burkhardt*

Abstract

I provide empirical evidence indicating that inflation risk is time-varying and priced in the cross-section of individual stocks in the U.S. and UK equity markets. I establish that the way inflation risk is priced in equity markets is closely related to the cyclicality of inflation. I show that the market price of inflation shocks is positive (negative) when inflation is procyclical (countercyclical) and hence comoves positively (negatively) with measures of economic activity. As a consequence, risk premiums on stocks with positive/negative exposure to inflation shocks depend on whether the economy is in a pro- or countercyclical inflation regime. A zero-investment strategy that goes long low (high) inflation-beta stocks and short high (low) inflation-beta stocks when inflation is countercyclical (procyclical) yields economically large and statistically significant return premiums in both markets, even after controlling for well-known risk-factors.

KEYWORDS: inflation risk, cyclicality of inflation, cross-section of stock returns

*I thank Henrik Hasseltoft, Thorsten Hens, Alexandre Ziegler, Kristoph Streikert and seminar participants at the University of Zurich for valuable input and helpful comments.

1 Introduction

Inflation is a central factor in every economy and exposure to inflation risk is important to all agents in an economy. High inflation reduces the purchasing power of consumers' nominal labor and capital income and can give rise to wage-price spirals. It reduces the real value of savings for retirement, it redistributes wealth from lenders to borrowers, and the liabilities of pension funds nominally increase with inflation. In the light of an unprecedented unconventional and expansive monetary policy in the U.S. and Europe over the last years, it is of high importance to know how inflation risk impacts financial markets and whether inflation risk can be hedged.

The literature examining whether inflation risk is priced in the cross-section of individual stocks is rather limited and constricted to the U.S. market. Estimating inflation-betas (the quantity of risk) to measure the exposure of individual stocks to inflation shocks and sorting the stocks into different portfolios based on their inflation-betas, Duarte (2013), Boons, de Roon, and Szymanowska (2012) and Ang, Brière, and Signori (2012) all conclude that inflation risk is priced in the cross-section of individual U.S. stocks.

Duarte (2013) for the period 1959 to 2009, and Boons, de Roon, and Szymanowska (2012) for the period 1964 to 2010 find that a zero-investment strategy going long (short) the portfolio containing the stocks with the lowest (highest) inflation-betas yields positive returns, indicating that stocks with low returns during inflationary times command a positive risk premium.[1] Employing the estimated inflation-betas to perform Fama and MacBeth (1973) regressions, Duarte (2013) finds the market price of inflation risk implied by the cross-section of U.S. stock returns to be negative, implying that positive inflation shocks correspond to bad states of nature on average. He concludes that assets exhibiting low excess returns when inflation is increasing must offer higher mean returns to compensate investors for bearing inflation risk. Conditioning on the size of the market for TIPS, the results in Boons, de Roon, and Szymanowska (2012) indicate that the inflation risk premium reverses and becomes negative with the introduction of the TIPS market around the turn of the century.[2]

[1]Duarte (2013) finds a premium of 1.75% per annum (not significantly different from zero), Boons, de Roon, and Szymanowska (2012) find an average return difference that varies between 1.5% and 5% per annum (depending on the portfolio formation procedure) and that cannot be explained by commonly used risk factors.

[2]They develop a CAPM model with exogenous, non-tradable risk to explain the reversal in the inflation risk

Opposed to Duarte (2013) or Boons, de Roon, and Szymanowska (2012), Ang, Brière, and Signori (2012), considering the more recent time period 1989 to 2010, find weak evidence suggesting that stocks with high inflation-betas have higher returns on average than stocks with low inflation-betas.[3]

The main contribution of this article is to provide empirical evidence indicating that inflation risk is time-varying in the cross-section of individual stocks in the U.S. and the UK equity markets, and that the way inflation risk is priced in these markets is closely related to whether the economy is in a pro- or countercyclical inflation state.[4] Employing three alternative out-of-sample signals that indicate whether the economy is in a pro- or countercyclical inflation regime, I empirically show that the market price of inflation shocks/risk is positive (negative) in the cross-section of U.S. and UK stocks when inflation is procyclical (countercyclical). As a consequence, risk premiums on stocks with positive/negative exposure to inflation shocks depend on whether inflation is pro- or countercyclical. When inflation is countercyclical, positive inflation shocks are suggestive of bad economic times and the market price of inflation risk is negative. Stocks with a highly positive (negative) exposure to inflation shocks yield high (low) real returns during inflationary times, are hence countercyclical (procyclical) and consequently command a negative (positive) inflation risk premium on average. If inflation is procyclical on the other hand, positive inflation shocks indicate good economic times and the market price of inflation risk is positive. Hence, stocks with a highly positive (negative) exposure to inflation shocks that yield high (low) real returns during inflationary times are subject to a positive (negative) inflation risk premium. This implies that a zero-investment strategy that goes long low (high) inflation-beta stocks and short high (low) inflation-beta stocks when inflation is countercyclical (procyclical) should yield positive returns on average.

premium and argue as follows: Before the introduction of TIPS, investors exposed to inflation are forced to hedge this risk largely in the stock market, thereby causing low inflation-beta stocks to outperform high inflation-beta stocks. After the introduction of TIPS, Boons, de Roon, and Szymanowska (2012) on p.4 claim: "If investors invest in TIPS and other inflation-linked assets to hedge inflation exclusively, the model implies that the inflation risk premium is zero. On the other hand, if TIPS are sufficiently attractive from a diversification (speculative) point of view as well, the model implies that the stock market-based inflation risk premium will reverse, because the incentive to hedge this speculative position will dominate in the stock market."

[3] Based on in-sample (out-of-sample) betas, the return difference between high inflation-beta stocks and low inflation-beta stocks is positive and equal to 3.76% (1.36%) per annum, which translates into a significant (insignificant) Carhart-alpha of 0.81% (0.27%) per month.

[4] Inflation is defined to be procyclical (countercyclical) if the correlation between inflation and measures of real economic activity, such as e.g. real consumption growth, real GDP growth or industrial production growth, is positive (negative).

This article contributes to the literature by relating the time variation of inflation risk premiums in the cross-section of individual equities to the cyclical nature of inflation. Instead of estimating the market price of inflation risk and inflation risk premiums over specific periods or subperiods as is custom in the existing literature, I employ out-of-sample signals in order to differentiate between pro- and countercyclical inflation periods and analyze the impact of inflation shocks conditional on inflation being pro- or countercyclical. The evidence provided in this article is able to reconcile the ambiguous findings with respect to the relation between inflation shocks and equity returns in the literature just discussed. I also find the market price of inflation risk to be negative and low inflation-beta stocks to outperform high inflation-beta stocks over sample periods similar to those in Duarte (2013) or Boons, de Roon, and Szymanowska (2012), and the opposite over more recent periods as e.g. those considered in Ang, Brière, and Signori (2012). This evidence conforms to the observation that the period between the 1960's and the early 2000's was predominantly characterized by countercyclical inflation, whereas the economy is in a predominantly procyclical inflation regime since around 2000. As Boons, de Roon, and Szymanowska (2012), I likewise find the inflation risk premium to switch its' prefix to negative around the turn of the last century. But instead of linking this change to the emergence of the TIPS market as they do, I show that it is instead a consequence of inflation entering a procyclical inflation regime in the early 2000's after having been countercyclical for several decades. Evidence relying on long-term data back to the 1940's moreover suggests that inflation was also procyclical and inflation risk premiums thus negative during the 1940's until the early 1950's, which makes the (anyway implausible) attempt to explain the switch in U.S. inflation risk premiums with the emergence of TIPS markets obsolete. To the best of my knowledge, this is the first study relating inflation risk in the cross-section of individual stocks to the changing cyclical nature of inflation and positing a rational explanation for how and why inflation risk changes over time.

Measuring the exposure of real returns on individual stocks to inflation shocks by estimating out-of-sample inflation-betas, I find that considered over the entire sample periods, stocks with a negative exposure to inflation shocks (negative inflation-betas) subsequently outperform stocks with a positive exposure to inflation shocks in both countries. This indicates that stocks with low returns during inflationary times command a positive risk premium on average over the considered time periods. In the U.S., the return differential between a portfolio containing stocks located in the lowest and a portfolio containing stocks located in the highest inflation-beta decile every month is statistically significant at the 10%-level and ranges between 0.41% and 0.48% per month, depending on the portfolio holding horizon. However, controlling for well-known risk factors absorbs most of this return premium such that the Carhart-alpha on a zero-investment portfolio that is long low and short high inflation-beta stocks is not significantly different from zero.[5] In the UK, the return difference between low and high inflation-beta stocks is also positive, but with 0.11% per month for holding the portfolios for one month rather small and, even before controlling for risk-factors, not statistically different from zero.

I employ three different out-of-sample signals that indicate whether the economy is in a pro- or countercyclical inflation regime and implement the following signal-based zero-investment strategy: If at the end of month t the signal indicates that inflation is countercyclical (procyclical), I go long the lowest (highest) inflation-beta stocks and short the highest (lowest) inflation-beta stocks. The returns resulting from this strategy confirm that inflation risk in equity markets is indeed closely related to the cyclicality of inflation. Whereas the zero-investment strategy that is always long low and short high inflation-beta stocks experiences major losses during procyclical inflation periods, employing the signals allows anticipating switches in the cyclicality of inflation in due time, such that the signal-based strategies are able to transform these losses into gains and consequently yield positive average returns over pro-, as well as over countercyclical inflation periods. In the U.S. and the UK, the signal-based strategies yield statistically highly significant and economically large average returns, even after controlling for well-known risk factors. Across all three signals, the average returns in the U.S. (UK) are between 0.79% and 0.94% (0.51% and 0.76%) per month, depending on the portfolio holding horizon. Controlling for risk factors yields statistically significant Carhart-alphas ranging between 0.57% and 0.75% (0.50% and 1.01%) per month in the U.S. (UK). The returns are consistently positive within subgroups of stocks and largest among stocks with high (low) market capitalization and high (low) book-to-market values in the U.S. (UK). All in all, inflation risk seems to be an impor-

[5] I name the zero-investment strategy that is always long low and short high inflation-beta stocks the "*unconditional inflation-beta strategy*" throughout this article.

tant component of risk premiums in the cross-section of U.S. and UK equities that cannot be explained by widely accepted risk factors.

This article is closely related to and motivated by the findings in Burkhardt and Hasseltoft (2012). Burkhardt and Hasseltoft (2012) empirically establish that the cyclicality of inflation varies over time and that changes in the cyclicality of inflation have important asset-pricing implications. They show that a number of relations between inflation and asset prices change over time and that these changes happen simultaneously to changes in the correlation between inflation and measures of real economic activity. For example, the correlations between aggregate stock and government bond returns are inversely related to the correlations between inflation and measures of economic activity. Furthermore, while an increase in inflation risk always depresses aggregate equity prices, it only depresses bond prices when inflation is countercyclical but increases them when inflation is procyclical. On the other hand, an increase in expected inflation depresses (increases) equity prices when inflation is countercyclical (procyclical) but always depresses bond prices.[6]

Burkhardt and Hasseltoft (2012) develop a long-run risk model featuring non-neutral inflation and a regime-switching mechanism allowing for counter- and procyclical inflation regimes, that rationalizes their empirical findings. In their model, the market price of inflation shocks is negative (positive) when inflation is countercyclical (procyclical)[7], while the impact of inflation shocks on real aggregate equity returns is negative (positive) when inflation is countercyclical (procyclical).[8] Consequently, inflation shocks make equity procyclical and agents ask a positive equity risk premium for bearing inflation risk, independently on whether inflation is pro- or countercyclical.[9]

Transferring this concept to individual stocks implies the following: While it is sensible that the impact of inflation shocks on aggregate stock returns is negative (positive) when inflation is countercyclical (procyclical), this is not necessarily the case on the level of individual stocks.

[6]These findings imply that inflation risk drives stock and bond returns in the same (opposite) direction if inflation is countercyclical (procyclical).

[7]Implying that agents dislike (like) inflation shocks when inflation is countercyclical (procyclical).

[8]Via a cash-flow channel in the model: Positive inflation shocks imply higher future growth when inflation is procyclical, which feeds into higher future aggregate dividend growth, causing higher current returns.

[9]In the model, the inflation risk premium basically is an average of the products of the market price of inflation shocks times the impact of inflation shocks on real equity returns across the two inflation regimes.

It is very well possible that the impact of inflation shocks on the real returns on individual equities (as e.g. quantified by inflation-betas that measure the exposure of stock returns to inflation shocks) varies across stocks. As the inflation risk premiums on individual stocks can be considered as the product of the impact of inflation shocks on their real returns times the market price of inflation shocks, this implies that stocks with a positive (negative) exposure to inflation shocks command a negative (positive) risk premium when inflation is countercyclical, and the opposite when inflation is procyclical.

The rest of the paper is organized as follows: I review additional literature on inflation risk and stock returns in Section 2. In Section 3, I describe the data and explain the methodology that I employ. Section 4 contains the results. U.S. results are summarized in Section 4.1, the results for the UK stock market are presented in Section 4.2. Section 5 eventually concludes. Tables and figures for the main results are provided in Section 6, robustness checks and supplementary results are contained in the Appendix.

2 Literature Review

In addition to the articles cited in the introduction, most literature on inflation risk in financial markets focuses on aggregate stock and bond market returns and the yield curve, not on individual stocks. According to Fisher (1930), the nominal interest rate can be decomposed into two components: The real interest rate and expected inflation. As Fama and Schwert (1977) point out, this decomposition can be applied to any asset return and any time horizon in efficient markets, such that the expected nominal return on any asset can be written as the sum of equilibrium expected real returns (which are determined by real factors) and expected inflation. If, as postulated by Fisher (1930), real and monetary sectors are essentially unrelated (implying real returns and expected inflation are independent), then nominal returns should move one-to-one with expected inflation and investors hence get compensated for changes in inflation/purchasing power. This is sometimes called the (generalized) Fisher hypothesis.

Fama and Schwert (1977) test the prediction of the Fisher hypothesis, as well as the relation between asset returns and unexpected inflation for various asset classes.[10] Employing data from 1953 to 1971, they conclude that the expected nominal (and real) returns on value- and equal-weighted portfolios containing all common NYSE stocks seem to be negatively related to expected and unexpected inflation and hence constitute poor hedges against both, expected and unexpected inflation. Solnik (1983), using stock market data from 1971 to 1980 for nine major stock markets or Gultekin (1983), employing stock market indices from 26 countries for the period 1947 to 1979, provide empirical evidence which confirms the findings of Fama and Schwert (1977).[11] Boudoukh and Richardson (1993), with annual data from 1800 to 1990, examine the relation between aggregate stock returns and inflation in the U.S. and the UK at longer time horizons and find evidence suggesting that at long horizons nominal stock returns are positively related to both ex-ante and ex-post long-term inflation, whereas at the one-year horizon the relation is negative. Pooling data for eight major countries for the period 1958 to 1996, Solnik and Solnik (1997) provide evidence supporting the findings of Boudoukh and Richardson (1993): The longer the horizon, the stronger the evidence in favor of a positive nominal stock return-inflation relation in line with the Fisher model.

More recently, Bekaert and Wang (2010) estimate inflation-betas for government bond and equity indices in 45 countries for the time period 1970 to 2010. They conclude that these securities, as well as foreign bonds, real estate and gold are poor hedges to expected and unexpected inflation - both in the short- and in the long-run. Their returns do not comove positively with inflation, and where a positive correlation is found - as e.g. for gold - it is weak. Especially in developed markets, real aggregate stock returns and inflation are mostly negatively correlated. In emerging markets on the other hand, aggregate stock returns and inflation are often positively correlated.

Schmeling and Schrimpf (2010) investigate the relation between survey-based expected infla-

[10]Fama and Schwert (1977) consider an asset to be a "complete hedge against inflation" if its' nominal return moves one-to-one with expected and unexpected inflation and if the ex-post real return is uncorrelated with the ex-post inflation rate.

[11]Earlier studies suggesting a negative relationship between stock returns and expected/unexpected inflation include a.o. Nelson (1976). Jaffe and Mandelker (1976) find mixed evidence for the U.S. From 1953 to 1971 they find a negative relation between expected inflation and stock returns, for the period 1875 to 1970 yearly stock returns appear to be unrelated to inflation.

tion and stock returns across six countries.[12] They find that expected inflation forecasts future aggregate real stock returns positively (in-sample and out-of-sample) in the considered major equity markets.

Moerman and van Dijk (2010), employing data from 1975 to 1998, estimate a conditional version of the ICAPM for France, Germany, Japan, the UK and the U.S. They find that inflation risk is an important source of systematic risk in international asset returns, which is priced because investors use part of their portfolio to hedge against domestic inflation risk. Assets with high returns during times with high inflation earn lower expected returns. Katzur and Spierdijk (2010) use data from 1985 to 2010 and analyze the exposure of common stocks to inflation risk and the impact of this exposure on portfolio choice. They find no/little empirical evidence against the Fisher hypothesis and show that stock allocations of investors who believe that real stock returns are unrelated to inflation and those believing in feedback between real stock returns and expected/unexpected inflation differ: The latter invest much less of their wealth in the stock index.

Overall, conclusions with respect to the relation between aggregate stock returns and inflation seem to depend on the considered time-period, country and methodology. By and large, most studies indicate that the correlation of expected/unexpected inflation and aggregate stock market returns is negative or non-existent. Despite these ambiguous results, this relationship is crucial to investors and central banks. And even if the aggregate stock market represents a rather poor inflation hedge, portfolios of individual stocks can nevertheless provide good inflation hedging capabilities.

3 Data and Methodology

3.1 Data

Monthly returns, prices, volume and market capitalization (price times shares outstanding) data for individual U.S. stocks and monthly value-weighted returns on all NYSE, AMEX and

[12]The U.S., the UK, Germany, France, Italy and Japan.

NASDAQ stocks (representing returns on a broad market index) are obtained from CRSP. I consider all common stocks in the CRSP universe with "Share Code" ≤ 11.[13] Book value data is from Compustat, available since the 1950's, and needed to calculate book-to-market ratios.[14] Risk factors (market, size, value, momentum) and risk-free rates are from Kenneth French's Data Library.[15] I collect monthly index returns on government bonds of various maturities from the "Index/Treasury and Inflation" files in the CRSP database - this data is available back to 1942.

The monthly Consumer Price Index (CPI) for all urban consumers is from the U.S. Bureau of Labour Statistics and available since 1913. Monthly U.S. Industrial Production Index and quarterly US Real GDP data are from Global Financial Data and start in 1919 and 1947, respectively.[16]

Return, price, volume, market capitalization and price-to-book data for individual stocks in the UK are collected from Datastream.[17] I consider all common equity stocks (companies' major securities and primary quotes only) that are traded on the public exchange in London. UK risk factors are from Gregory, Thayaran, and Christidis (2013) and start in October 1980.[18] As a broad stock market index I employ the FTSE All-Share Index and monthly risk-free rates are calculated from the UK Total Return Bills Index - all these data series are from Global Financial Data. Total return indices on 10-year UK government bonds are also from Global Financial Data, total return indices for government bonds with maturities ranging from one to three years and for 2-, 5-, 20- and 30-year maturities are collected from Datastream.

All economic data series for the UK are obtained from Global Financial Data. Inflation data is based on the monthly UK Retail Price Index, for monthly data on industrial production I use the UK Industrial Production Index (Global Financial Data collect both series from the Office

[13]Ordinary common shares of companies incorporated in the U.S. Companies incorporated outside the U.S., trusts, closed-end funds and REIT's are excluded.
[14]As in Fama and French (1993), I compute the book-to-market ratio used in June of year t as the ratio of the book value for the fiscal year ending in calendar year t-1 and the market capitalization as of December of year t-1.
[15]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[16]Global Financial Data collect the U.S. Industrial Production Index (USINDPROM) and quarterly U.S. Real GDP (GDPCUSA) from the Federal Reserve Bank of St.Louis' FRED database.
[17]UK stock data (returns, prices, market capitalization) in Datastream starts in 1969, price-to-book data is not available before 1980 (Worldscope).
[18]See http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/files/.

for National Statistics) and quarterly data on real growth is approximated using the quarterly UK Real GDP series.[19]

3.2 Methodology

3.2.1 Estimating Inflation-Betas

I estimate inflation-betas in order to measure the exposure of individual stocks to unexpected inflation (inflation shocks). I proxy unexpected inflation by the monthly change in the annual inflation rate.[20] Hence, the month t unexpected inflation is calculated as $\triangle\pi_t = \pi_t - \pi_{t-1} = \frac{CPI_t}{CPI_{t-12}} - \frac{CPI_{t-1}}{CPI_{t-13}}$. This procedure to calculate a monthly series of unexpected inflation is common in the literature, see e.g. Bekaert and Wang (2010), Duarte (2013), or Boons, de Roon, and Szymanowska (2012) and the references therein.[21]

In order to get an estimate at time t of the exposure of stock n to inflation shocks I calculate inflation-betas $\hat{\beta}_{n,t}$. In each month $t = 1, ..., T$ and for each stock $n = 1, ..., N$ in my sample, I regress the series of monthly stock excess returns (real returns by definition) on unexpected inflation. As e.g. Duarte (2013) or Boons, de Roon, and Szymanowska (2012), I employ a weighted least-squares (WLS) regression with an expanding estimation window and exponentially decaying weights with a half-life of five years.[22] This approach makes use of all available observations and hence of as much information as possible and at the same times gives more weight to more recent observations:

$$(\hat{\alpha}_{n,t}, \hat{\beta}_{n,t}) = argmin_{\alpha_{n,t},\beta_{n,t}} \sum_{\tau=1}^{t-1} K(t-\tau)(R_{n,\tau} - R^f_\tau - \alpha_{n,t} - \beta_{n,t}\Delta\pi_\tau), \tag{1}$$

[19]The UK Retail Price Index is available since 1914, the UK Industrial Production Index since 1956, UK Real GDP data since 1955.

[20]Alternative measures for unexpected inflation - e.g. monthly or annual inflation shocks extracted from an AR(1) model, or the monthly change in monthly inflation rates - yield similar results.

[21]Citing from p.4 in Bekaert and Wang (2010): "While this random walk model for inflation may appear inconsistent with the data, we suspect it is hard to beat by more complex models in out-of-sample forecasting. In fact, for the US, Atkeson and Ohanian (2001) show as much."

[22]Adding commonly used risk factors to the regression when estimating $\hat{\beta}_{n,t}$, using Vasicek (1973)-adjusted betas or simply estimating $\hat{\beta}_{n,t}$ using OLS with a constant estimation window of 60 months does not change the qualitative nature of the results.

with weights $K(t-\tau) = \frac{exp(-|t-\tau-1|h)}{\sum_{\tau=1}^{t-1} exp(-|t-\tau-1|h)}$ and $h = \frac{log(2)}{60}$.

For a stock to be considered in the month t estimation, it is required to have at least 50 monthly observations. Moreover, because the CPI series is not announced until the middle of the subsequent month, I only use data up to month $t-1$ when estimating $\hat{\beta}_{n,t}$. This ensures that there is no look-ahead bias and that the inflation-betas can be used for out-of-sample tests.

3.2.2 Forming Inflation-Beta Portfolios

In order to evaluate whether inflation risk is priced in the cross-section of individual stocks in the U.S. and the UK, I test for systematic return differentials between stocks with low and stocks with high inflation-betas. I exclude stocks with prices in the first price decile at the end of each month in the respective countries to make sure that the results are not driven by small illiquid stocks.[23] Furthermore, stocks are required to be actively traded during the portfolio formation month and to have price and market capitalization data to be included in the universe of investable stocks that I consider in month t.

At the end of each month t, I sort the investable stocks in each country according to their inflation-betas $\hat{\beta}_{n,t}$. Employing the deciles of the inflation-beta distribution at time t, I split the stocks into ten portfolios. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months (portfolio holding periods).[24]

To examine the existence of an unconditional return premium for bearing inflation risk I construct a zero-investment portfolio that goes long portfolio 1 and short portfolio 10, and evaluate the resulting time-series of monthly zero-investment portfolio returns against the CAPM-, the Fama-French- and the Carhart-factors. I name this long-short strategy the "*unconditional inflation-beta strategy*" throughout this article.

I also examine return differentials between low and high inflation-beta portfolios within sub-

[23]U.S. results for excluding stocks with prices below \$5 instead are qualitatively and quantitatively very similar. They are available from the author upon request.

[24]As e.g. Fama (1998), I use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Results for using equal-weighted returns are qualitatively similar. For the sake of brevity I only report results based on value-weighted returns in this article.

groups of stocks. To do so, I first sort all stocks into terciles according to their market capitalization, book-to-market value and industrial production beta at the end of each month t.[25] Within each of the resulting terciles I form ten inflation-beta portfolios and construct a zero-investment portfolio that goes long portfolio 1 and short portfolio 10. I calculate the subsequent returns on the long-short portfolio and evaluate the resulting monthly returns against the risk factors.

3.2.3 Signals

I employ three alternative out-of-sample signals to determine whether the economy is in a pro- or countercyclical inflation state. Two of them rely on correlations between measures of economic activity and inflation. Burkhardt and Hasseltoft (2012) also establish that stock-bond correlations are inversely related to the correlations between measures of economic activity and inflation. Consequently, the third signal that I employ is based on correlations between aggregate stock returns and government bond returns. When implementing these signals, I ensure that there is no look-ahead bias, such that an investor, at any point in time t during the considered sample period, could in fact have implemented this strategy in reality.

The first signal is based on rolling correlations between yearly real GDP growth and yearly inflation. At the end of each quarter t, I compute the correlation between a quarterly series of yearly real GDP growth and a quarterly series of yearly inflation, using k quarters of data. As neither real GDP growth, nor inflation are observable in real time, I calculate the correlation (signal) for quarter t by only considering data that was available as of quarter $t-1$, hence quarterly data from quarter $t-k$ to quarter $t-1$.[26] If the resulting correlation is positive (negative) at time t, I consider the economy to be in a procyclical (countercyclical) inflation state.

The second signal that I employ relies on an alterative measure of economic activity. It is based on rolling correlations between a monthly series of yearly industrial production growth and a monthly series of yearly inflation, utilizing k months of data to calculate the correlations.

[25]Terciles are used to guarantee an adequate number of stocks in the portfolios. Industrial production betas are calculated in the same way as inflation-betas, see equation (1). They proxy the exposure to shocks in industrial production growth. Stocks that are more sensitive to shocks in economic activity are expected to also be more responsive to inflation shocks.

[26]The signal at the end of quarter t is then employed for months t to $t+2$.

To ensure that the signal can be used out-of-sample, I only consider monthly data from month $t-k$ to month $t-1$ to calculate the signal for month t. And as above, if the resulting correlation is positive (negative) at time t, I consider the economy to be in a procyclical (countercyclical) inflation state.

As a third signal I use (smoothed) rolling correlations between a monthly series of yearly returns on a broad U.S. equity market index and a monthly series of yearly returns on a one-year U.S. government bond index.[27] Stock market returns are approximated by the value-weighted returns on all NYSE, AMEX and NASDAQ stocks. At the end of each month, I calculate the correlation between monthly series of yearly stock and bond returns using k months of data. The signal that is in use for month t is then computed as the 24-month moving average of the resulting correlations. If the resulting signal is negative (positive) at time t, I consider the economy to be in a procyclical (countercyclical) inflation state.

3.2.4 Fama-MacBeth Regressions

Burkhardt and Hasseltoft (2012) show that the cyclicality of inflation changes over time. As explicated in Section 1, these changes are expected to influence the nature of inflation risk in equity markets. Therefore, I evaluate whether the market price of inflation risk changes its' prefix when the economy moves from a counter- to a procyclical inflation state. To do so, I perform cross-sectional Fama and MacBeth (1973) regressions. To get an estimate of the market price of inflation risk over the entire sample period, I make use of the inflation-betas estimated according to equation (1). For every month t, I run a cross-sectional regression of the excess returns ($R^e_{n,t} = R_{n,t} - R^f_t$) on the n stocks that are in the universe of investable stocks (as defined above) in month t onto a constant and their time t inflation-betas ($\hat{\beta}_{n,t}$) from equation (1):

$$R^e_{n,t} = \gamma_t + \lambda_t \hat{\beta}_{n,t} + \varepsilon_t, \ n = 1, ..., N. \tag{2}$$

[27] The strategy also works if the signal is based on the returns on government bonds of longer maturities.

The resulting estimates $\hat{\gamma}_t$ and $\hat{\lambda}_t$ are averaged over time ($\overline{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t$ and $\overline{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t$) and tested for statistical significance. To get an estimate of the market price of inflation risk for pro-/counteryclical inflation states separately, I run equation (2) by only considering the months t for which the respective signal indicates pro-/counteryclical inflation states.

3.2.5 Signal-Based Strategy

According to the argumentation in Section 1, stocks with positive (negative) inflation-betas should command a negative (positive) risk premium if inflation is countercyclical, implying that a strategy that goes long the stocks with the lowest and short those with the highest inflation-betas should yield positive returns on average. If inflation is procyclical on the other hand, things reverse: Stocks with positive (negative) inflation-betas should command a positive (negative) risk premium and a strategy that goes long the stocks with the highest and short those with the lowest inflation-betas should yield a positive return premium on average. Thus, to further analyze the implications of changes in the cyclicality of inflation on the way inflation risk is priced in the cross-section of individual equities, I test this strategy.

I apply the three signals to the unconditional zero-investment strategy outlined above: Instead of always being long/short the portfolio containing the stocks with the lowest/highest inflation-betas, I reverse the long- and short-positions when the signals indicate a procyclical inflation state at the time I form the inflation-beta portfolios. Thus, if at the end of month t the signal indicates that inflation is countercyclical (procyclical), I go long the lowest (highest) inflation-beta stocks and short the highest (lowest) inflation-beta stocks. The resulting time-series of monthly zero-investment portfolio returns for different portfolio holding horizons are evaluated against the CAPM-, the Fama-French- and the Carhart-factors.

4 Results

I present my findings in two sections. Section 4.1 contains the results for the U.S., in Section 4.2 I summarize the results for the UK stock market. In each section, I first estimate the market prices of inflation shocks for the entire sample period and for the pro- and countercyclical inflation states, respectively. Then, I compare the returns on the unconditional inflation-beta strategy to those on the three signal-based inflation-beta strategies.

4.1 Inflation Risk in the U.S. Equity Market

In this section, the focus is on inflation risk in the U.S. equity market during the period 1965 to 2013. Detailed results corresponding to this sample period can be found in Tables I to XIII. For robustness, I also present results for the periods 1940 to 2013 and 1952 to 2013 - they are contained in Sections A.2 and A.3 of the Appendix and demonstrate that the cyclicality of inflation also matters during these earlier periods.[28]

Table I presents summary statistics on the portfolios that result from employing the inflation-beta distribution at the end of each month t to partition the stocks into ten portfolios. The ten portfolios are held for one month, are rebalanced monthly and contain about 282 stocks on average in each month (see column five). As explained in Section 3.1, portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. Column two of Table I reports the average inflation-betas for the stocks in each of the ten portfolios. The average inflation-betas vary considerably across the portfolios; whereas the stocks in portfolio 1 exhibit a negative average inflation-beta of -11.59, those contained in portfolio 10 exhibit a positive average beta of 6.30. Column three displays that the average portfolio returns increase almost monotonically with decreasing inflation-betas and that the return difference between portfolios 1 and 10 amounts to economically relevant 0.48% per month. This is in line with the evidence presented in Duarte (2013) or Boons, de Roon, and Szymanowska (2012) and indicates that stocks with low returns during inflationary times (stocks whose returns are negatively correlated to inflation shocks) command a positive risk premium on average over the considered time period. The standard deviations of the portfolio returns, given in column four, are highest for the extreme portfolios 1 and 10. The last column of Table I displays the average turnover for each portfolio.[29] The

[28]Quarterly data on U.S. real GDP starts in 1947. Starting in 1965 guarantees a sufficient number of data points for the calculation of all three signals that I employ. Hence, for the 1952 to 2013 period I only report results for signals that are based on correlations between industrial production growth and inflation and between stock and bond returns, respectively. For the 1940 to 2013 period I only report results for the signal that is based on correlations between industrial production growth and inflation.

[29]Turnover (ignoring price fluctuations) is calculated as $T = (n1 - n3)/n1 + (n2 - n3)/n2 + n3 * abs(1/n1 - 1/n2)$, with $n1$ ($n2$) denoting the number of stocks in the portfolio in month t ($t+1$) and $n3$ representing the number

turnover is lowest for portfolios 1 and 10, suggesting that the composition of these portfolios is relatively stable and does not involve excessive trading.

In order to analyze whether inflation risk in equity markets is indeed closely related to the cyclicality of inflation, I now apply the out-of-sample signals that indicate whether the economy is in a pro- or countercyclical inflation state and evaluate how the market price of inflation risk changes with the cyclicality of inflation.

4.1.1 Fama-MacBeth Regressions

Table II contains the estimates and corresponding p-values resulting from the Fama and MacBeth (1973) cross-sectional regressions described in Section 3.1. I focus on estimates of $\overline{\lambda}$, which can be interpreted as market prices of inflation risk. Over the entire sample period 1965 to 2013, the market price of inflation risk is negative, albeit not significantly so. This is in line with the evidence reported in e.g. Duarte (2013) or Boons, de Roon, and Szymanowska (2012). Hence, considered over the entire sample, high inflation-beta stocks yield lower excess returns on average, which suggests that positive inflation shocks correspond to bad states of nature on average. As high inflation-beta stocks yield high real returns during inflationary times, this implies that their returns are countercyclical and thus subject to a negative return premium compared to low inflation-beta stocks. Investors are ready to accept lower average returns on stocks that provide insurance against inflation shocks (high inflation-beta stocks). Or stated differently, investors need to be compensated for bearing inflation risk: They are only ready to hold assets that yield low returns when inflation is high (low inflation-beta stocks), if these assets compensate them with higher mean returns.

Running the Fama and MacBeth (1973) regressions separately for the pro- and countercyclical inflation states as indicated by the three signals yields a consistent pattern across all three signals. During the months for which the signals indicate that inflation is countercyclical, the market price of inflation risk $\overline{\lambda}$ is significantly negative. If inflation is procyclical on the other hand, the resulting market price of inflation risk $\overline{\lambda}$ is always positive, and significantly so for the signals that are based on rolling correlations between the two measures of economic activity and

of stocks in the portfolio in both months.

inflation. A positive market price of inflation risk implies higher excess returns on high inflation-beta stocks. During inflationary times, these stocks yield high returns. As inflationary times correspond to good states of nature if inflation is procyclical, this means that the returns on high inflation-beta stocks are procyclical and hence subject to a positive risk premium relative to low inflation-beta stocks. Thus, investors do not require compensation for bearing inflation risk if inflation is positively correlated with measures of economic activity and a zero-investment portfolio long high and short low inflation-beta stocks should yield positive returns on average.

To analyze whether these changes in the market price of inflation risk actually become manifest in risk premiums on individual equities in the anticipated manner, I compare the returns on the unconditional inflation-beta strategy to those on the three signal-based strategies. I start with the signals that rely on correlations between measures of economic activity and inflation.

4.1.2 Signals I: Economic Activity - Inflation Correlations

The first signal that I employ is the one based on rolling correlations between quarterly series of yearly real GDP growth and yearly inflation. I present detailed results on the signal-based strategy, implemented using $k = 36$ quarters of data to calculate the signal, in Tables III to V. Table I in the Appendix contains a summary of the signal-based strategy results when the strategy is implemented using k quarters of data to calculate the rolling correlations between real GDP growth and inflation, with k ranging from 12 to 61 quarters.

Table III compares the returns on the unconditional zero-investment strategy that is always long the lowest and short the highest inflation-beta stocks to the returns resulting from the signal-based zero-investment strategy that goes long the lowest (highest) inflation-beta stocks and short the highest (lowest) inflation-beta stocks if the signal at the end of month t indicates that inflation is countercyclical (procyclical). The results displayed in Table III are for a portfolio holding period equal to one month. Whereas the signal-based long-short strategy yields a statistically highly significant and economically meaningful Carhart-alpha of 0.73% per month (8.76% per annum), simply being long low and short high inflation-beta stocks does not generate significant alphas (see left side of Panel 1). Moreover, as can be seen in Panels 2 and

3, the long-leg of the signal-based strategy consistently yields significantly positive, the short-leg significantly negative alphas, such that both legs contribute in a significant manner to the observed return premium.

Table IV summarizes the return premiums on both strategies for portfolio holding periods ranging from 1 to 12 months. Time-series means, CAPM-, Fama-French-, Carhart-alphas and annualized Sharpe ratios are reported. Two-sided p-values from Newey-West standard errors are given in parentheses. The signal-based long-short strategy yields significant and large return premiums ranging from 0.94% per month at the one-month horizon to 0.77% per month for holding the portfolios for one year. Herewith, the premiums are roughly twice as large as those on the unconditional long-short strategy (see left part of the table). The resulting Carhart-alphas are statistically highly significant at all holding horizons and between three to four times larger than the corresponding Carhart-alphas from the unconditional long-short strategy, which are not statistically different from zero. Annualized Sharpe ratios on the signal-based strategy are around 0.5, significantly different from zero at all considered portfolio holding horizons, and about twice as large as those on the unconditional inflation-beta strategy. In addition, the Sharpe ratios on the signal-based strategy are significantly different from those on the unconditional long-short strategy at the one-, three-, six- and nine-month portfolio holding horizons.[30]

Within terciles of stocks formed according to market capitalization, book-to-market value and industrial production beta, the signal-based strategy also robustly yields positive returns that are superior to those on the unconditional inflation-beta strategy (see Table V). The signal-based strategy yields the highest returns among large cap stocks, among stocks with high book-to-market values and among stocks with medium to low sensitivity to shocks in industrial production, but also yields significant return premiums after controlling for risk-factors among medium sized firms and among companies with low book-to-market values.

Table I in the Appendix contains the CAPM-, Fama-French- and Carhart-alphas (and the corresponding p-values) of the signal-based strategy that result when it is implemented using k

[30]Two-sided p-values for the $H0$ of equal Sharpe Ratios are 0.042, 0.038, 0.049, 0.076 and 0.106 for the 1-, 3-, 6-, 9- and 12-month portfolio holding horizons. To test for equality of Sharpe ratios, I use the heteroskedasticity and autocorrelation robust test statistic, as developed on p.851 $-$ 852 in Ledoit and Wolf (2008), employing the Newey and West (1994) method.

quarters of data to calculate rolling correlations between real GDP growth and inflation, with k ranging from 12 to 61 quarters. The displayed results are for a portfolio holding horizon of one month. The table illustrates that the signal-based strategy robustly yields significant and economically large alphas over a wide range of alternative lags k.

The return premiums resulting from applying the second signal, which relies on rolling correlations between monthly series of yearly industrial production growth and yearly inflation, are summarized in Tables VI to VIII. As for the real GDP growth - inflation based signal I present detailed results for a lag of $k = 108$ months (which corresponds to the 36 quarters of data I employed above). Table II in the Appendix contains a summary of the CAPM-, Fama-French- and Carhart-alphas of the signal-based strategy that result when employing an alternative number of lags k to calculate the signal. The table contains results for k ranging from 34 to 180 months and illustrates that the strategy robustly delivers significant and economically large alphas over a wide range of lags k.

Overall, the results are qualitatively very similar to those obtained when using real GDP growth - inflation correlations to indicate whether inflation is pro- or countercyclical. Table VI shows that both, the long- and short-legs of the signal-based strategy contribute in a significant manner to the observed alphas, although the returns on the short-leg are of a larger absolute magnitude. The returns on the signal-based strategy are slightly lower, but still highly significant at all horizons and with 0.87% (0.69%) per month at the one-month (one-year) portfolio holding horizon of economically relevant magnitudes (see Table VII). Annualized Sharpe ratios are around 0.5 and statistically significant. The alphas resulting after controlling for market-, size-, book-to-market- and momentum-factors remain statistically highly significant and close to those reported in Table IV. They range from 0.76% per month at the one-month horizon to 0.52% per month at the one-year portfolio holding horizon.

4.1.3 Signals II: Stock - Bond Correlations

As a third signal, I employ smoothed rolling correlations between monthly series of yearly returns on a broad U.S. equity market index and yearly returns on a one-year U.S. government bond index. If the resulting signal is negative (positive) at time t, I consider the economy to be in a procyclical (countercyclical) inflation state and go long the highest (lowest) and short the lowest (highest) inflation-beta stocks. I present detailed results for a lag equal to $k = 60$ months in Tables IX to XI and a summary of the CAPM-, Fama-French- and Carhart-alphas that result when utilizing an alternative number of lags k to calculate the correlations in Table III in the Appendix (for lags k ranging from 34 to 180 months).

As for the economic activity-inflation correlation based signals, both, the long- and the short-leg of the signal-based strategy yield significant alphas and hence contribute to the overall performance of the strategy (see Table IX). The return premiums for holding periods between one month and one year are given in Table X. They are slightly larger than for the last two signals, and with 1.02% per month at the one-month horizon and 0.92% per month for holding the positions for one year highly significant and more than twice as large as the returns on the unconditional zero-investment strategy. After controlling for commonly used risk factors, the differences between the unconditional and the signal-based strategy are even more explicit: With 0.77% at the one-month to 0.67% at the one-year portfolio holding horizon, the Carhart-alphas on the signal-based long-short strategy are between four to more than six times as large as those on the unconditional long-short strategy. The alphas are of an economically large magnitude and statistically highly significant. As Table XI illustrates, the signal-based strategy returns are largest among large caps, among value stocks and among the stocks that are most reactive to shocks in economic activity. Table III in the Appendix eventually demonstrates that the signal-based strategy yields significant and large alphas not only when a lag of $k = 60$ months is employed to compute the signal, but also over a wide range of alternative lags k. This again confirms the stability of the presented results.

4.1.4 Equal-Weighted Portfolio across all Signals

In Tables XII and XIII, I present the returns on a portfolio that takes equal-weighted positions in the three presented signal-based zero-investment strategies by investing one third into each of them.

Table XII contains the corresponding results for portfolio holding periods ranging from one month to one year. Average returns and alphas become even more significant compared to those from the individual signal-based strategies: All two-sided p-values are clearly below 1%, average return premiums and Carhart-alphas are economically large and significant. The annualized Sharpe ratios increase to around 0.6, are hence more than twice as large as those on the unconditional inflation-beta strategy and they are statistically different from zero. Moreover, the difference in Sharpe ratios between the unconditional and the equal-weighted signal-based strategy is significant at the 5% level for all portfolio holding horizons.[31]

Within subgroups of stocks formed according to market capitalization, book-to-market value and industrial production beta, the equal-weighted strategy across all three signals consistently yields positive returns that are larger than those on the unconditional long-short strategy. Among stocks with medium to large market capitalization, as well as among stocks with low and high book-to-market values and among all industrial production beta terciles, the portfolio yields large and statistically significant positive return premiums.

Figure 1 plots the cumulative log-returns on the three presented signal-based strategies, as well as on the portfolio that takes equal-weighted positions in all three signal-based long-short strategies against the cumulative log-returns on the unconditional inflation-beta strategy. The plot is for a portfolio holding horizon equal to one month and illustrates the superior performance of the signal-based strategies since the early 2000's, when inflation turned procyclical after having been predominantly countercyclical for several decades.

The evidence presented so far is confirmed by the results based on the two longer sample periods 1940 to 2013 and 1952 to 2013, respectively, which are contained in the Appendix (Sections A.2 and A.3, respectively). For both periods, the market price of inflation risk is positive (negative) when the signals indicate procyclical (countercyclical) inflation states and employing the signals yields economically large and statistically significant returns. For the 1940 to 2013 period for example, the signal-based strategies yield average returns (Sharpe ratios) of

[31]Two-sided p-values for the $H0$ of equal Sharpe Ratios are 0.015, 0.012, 0.013, 0.021 and 0.032 for the 1-, 3-, 6-, 9- and 12-month portfolio holding horizons. To test for equality of Sharpe ratios, I use the heteroskedasticity and autocorrelation robust test statistic, as on p.$851-852$ in Ledoit and Wolf (2008), employing the Newey and West (1994) method.

8.4% (0.5) per year, compared to 3.1% (0.17) for the unconditional long-short strategy.

Moreover, as Burkhardt and Hasseltoft (2012) point out "... the comovement between inflation and growth has varied considerably. In particular, the 1930's experienced a strong positive comovement as The Great Depression was associated with low growth coupled with deflation. The positive correlation was further exacerbated by the strong rebound in growth and inflation starting in 1933. In contrast, the US economy underwent a stagflationary period in the 1970's and early 1980's. Growth and inflation started to comove positively again around the year 2000."[32] Figure 1 in the Appendix displays the cumulative log-returns on the signal-based and on the unconditional inflation-beta strategies for the 1940 to 2013 period and visualizes the cited observations. During the procyclical periods from the 1940's to the 1950's and in the 2000's, the unconditional strategy experiences severe losses, which is in line with the postulated relation between the cyclicality of inflation and inflation risk premiums and hence to be expected. As the cumulative log-returns on the signal-based strategies illustrate, the out-of-sample signals anticipate switches in the cyclicality of inflation in due time, such that the signal-based strategies yield positive returns over both, pro- and countercyclical inflation periods.

All in all, the results presented for the U.S. equity market are consistent with my hypothesis that the compensation for bearing inflation risk is time-varying and dependent on the cyclical nature of inflation. Moreover, they indicate that the three signals are able to properly capture pro- and countercyclical inflation states.

4.2 Inflation Risk in the UK Equity Market

I perform the same analysis as for the U.S. equity market in the UK. The time period I consider is from 1980 to 2013.[33] Tables XIV to XXVI contain the corresponding results.

Table XIV displays summary statistics on the ten inflation-beta portfolios in the UK. They are formed by employing the deciles of the inflation-beta distribution at the end of each month t to sort the set of investable stocks into ten groups. The corresponding portfolios are held for

[32]See p.8, Burkhardt and Hasseltoft (2012).

[33]I start in 1980 due to the restrictions on book-to-market and risk factor data for the UK. Time-series on both data categories are not available before 1980.

one month and rebalanced monthly. The average inflation-betas for the stocks in each of the ten portfolios vary considerably, though less than in the U.S. market (see column two of Table XIV). The stocks contained in portfolios 1 to 6 exhibit negative inflation-betas on average, ranging from -6.54 for portfolio 1 to -0.25 for portfolio 6. The remaining portfolios exhibit positive inflation-betas on average. The average inflation-beta is equal to 5.77 for portfolio 10, and the difference in inflation-betas between portfolios 1 and 10 amounts to -12.31. Opposed to the U.S., the average returns on the ten portfolios - displayed in column three - do not increase monotonically with decreasing inflation-betas. Portfolio 10, containing the stocks with the largest inflation-betas, still yields the lowest average returns, but the highest average returns are not those on portfolio 1. Nevertheless, the return difference between portfolios 1 and 10 is positive and amounts to 0.11% per month (compared to 0.48% per month in the U.S.), suggesting that stocks with low returns during inflationary times command a positive risk premium on average over the considered time period. As in the U.S., the standard deviations of the portfolio returns (column four) are highest for the extreme portfolios 1 and 10, while the turnover (last column) is lowest for these portfolios, indicating that the composition of portfolios 1 and 10 is relatively stable and does not involve excessive trading. On average, each of the ten portfolios contains 116 stocks each month (see column five).

The three alternative out-of-sample signals that indicate whether the economy is in a pro- or countercyclical inflation state are constructed as described in Section 3.1, but naturally with UK data. The first two signals that I consider are based on rolling correlations between measures of economic activity and inflation. Hence, a negative (positive) value signals that inflation is countercyclical (procyclical) and triggers a long position in the portfolio containing the lowest (highest) inflation-beta stocks and a short position in the portfolio composed of the highest (lowest) inflation-beta stocks.

4.2.1 Fama-MacBeth Regressions

Table XV contains the Fama and MacBeth (1973) cross-sectional regression estimates and the corresponding two-sided p-values. Over the entire sample period 1980 to 2013, the market price of inflation risk in the UK is negative, albeit not significantly so. Hence, considered over the entire sample, high inflation-beta stocks yield lower excess returns on average, which suggests that positive inflation shocks correspond to bad states of nature on average. As in the U.S., high inflation-beta stocks yield high real returns during inflationary times, implying that their returns are countercyclical and thus on average subject to a negative return premium compared to low inflation-beta stocks.

Running the Fama and MacBeth (1973) regressions separately for the counter- and procyclical inflation states as indicated by the three signals, again yields a consistent pattern across all three signals. During the months for which the signals indicate that inflation is countercyclical, the market price of inflation risk $\overline{\lambda}$ is negative. If inflation is procyclical on the other hand, the resulting market price of inflation risk $\overline{\lambda}$ is always positive.

4.2.2 Signals I: Economic Activity - Inflation Correlations

Detailed results on the signal-based strategy, implemented using $k = 48$ quarters of data to calculate the rolling correlations between the quarterly series of yearly real GDP growth and yearly inflation, are presented in Tables XVI to XVIII.[34]

A comparison of the risk-adjusted returns on the unconditional zero-investment strategy to those on the signal-based strategy is presented in Table XVI (for a portfolio holding period of one month). The resulting Carhart-alpha of the signal-based strategy amounts to statistically highly significant 1.01% per month (see right side of Panel 1). Opposed to the U.S., it is only the short-leg that significantly contributes to the large overall return premium, while the alphas on the long-leg are not statistically different from zero and of a relatively small absolute magnitude.

Table XVII compares the return premiums on the unconditional to those on the signal-based strategy for portfolio holding periods ranging from 1 to 12 months. Whereas the average monthly returns and annualized Sharpe ratios on the unconditional strategy are small and not statistically distinguishable from zero, the signal-based strategy yields average returns ranging from 0.76% per month at the three-month horizon to 0.50% per month at the one-year portfolio holding horizon. The average returns, as well as the CAPM-, Fama-French- and Carhart-alphas are all

[34]For completeness I also present results for $k = 36$ quarters (as for the U.S.) in Table XVII in Section A.4 of the Appendix. The results are qualitatively similar, but slightly weaker than for employing $k = 48$ quarters of data.

statistically significant and of economically relevant magnitudes. The Sharpe ratios are between 0.36 and 0.48 per annum and significantly different from zero.[35] Average returns, Carhart-alphas and Sharpe ratios on the signal-based strategy are more than six times larger than those on the unconditional strategy at all holding horizons.

Double-sort results are shown in Table XVIII. Opposed to the unconditional strategy, the signal-based strategy yields positive returns across all considered terciles. The premiums are largest among small and middle-sized companies, among stocks with low book-to-market values and among stocks with a high exposure to industrial production shocks.

Alphas on the signal-based strategy implemented using k quarters of data to calculate rolling correlations between yearly real GDP growth and yearly inflation, with k ranging from 12 to 61 quarters, are contained in Table XVI in the Appendix. It is apparent that the signal-based strategy yields significant and economically large return premiums over a wide range of alternative lags, even after controlling for common risk factors.

The return premiums resulting from applying the second signal, which relies on rolling correlations between monthly series of yearly industrial production growth and inflation, are summarized in Tables XIX to XXI. I present detailed results for a lag of $k = 144$ months.[36] Table XVIII in the Appendix contains an overview over the corresponding results for k ranging from 34 to 180 months and illustrates that the signal-based strategy yields significant and economically large alphas over a wide range of alternative lags k.

All in all, the results from employing this second signal are very similar - both qualitatively and quantitatively - to those obtained when using real GDP growth to compute the signal. Average returns on the signal-based strategy are statistically significant at all holding horizons, fluctuate between 0.54% and 0.79% per month and yield annualized Sharpe ratios between 0.38 and 0.50. Carhart-alphas vary between 1.05% per month for holding the portfolio one month to 0.54% per month when holding the portfolio for one year.

[35]Two-sided p-values for the $H0$ of equal Sharpe Ratios for the unconditional and signal-based strategies are 0.101, 0.044, 0.039, 0.075 and 0.090 for the 1-, 3-, 6-, 9- and 12-month portfolio holding horizons. To test for equality of Sharpe ratios, I use the heteroskedasticity and autocorrelation robust test statistic, as developed on p.851 − 852 in Ledoit and Wolf (2008), employing the Newey and West (1994) method.

[36]The $k = 144$ months of data correspond to the 48 quarters of data that I employed for the real GDP growth - inflation based signal in the UK. Results for $k = 108$ months, corresponding to 36 quarters of data, can be found in Table XIX in Section A.4 of the Appendix.

4.2.3 Signals II: Stock - Bond Correlations

Detailed results for utilizing $k = 60$ months of data to calculate the signal based on (smoothed) rolling correlations between monthly stock market and government bond returns are given in Tables XXII to XXIV. A summary of the CAPM-, Fama-French- and Carhart-alphas that result when utilizing k months of data to calculate the correlations - with k ranging from 34 to 180 months - is contained in Table XX in the Appendix. Table XX demonstrates that the signal-based strategy robustly yields significant and large alphas not only for a lag of $k = 60$ months, but also over a wide range of alternative lags k.

As for the economic activity - inflation correlation based signals it is mainly the short-leg of the signal-based long-short strategy that contributes to the overall performance of the strategy (see Panels 2 and 3 in Table XXII). The return premiums, Sharpe ratios and factor alphas for portfolio holding periods between one month and one year, which are summarized in Table XXIII, are also very close, both in terms of numbers and significance, to those obtained when employing the economic activity-inflation correlations based signals. The Carhart-alphas are between 0.99% per month for a one-month and 0.48% per month for a one-year portfolio holding period, statistically significant and economically meaningful.

4.2.4 Equal-Weighted Portfolio across all Signals

Tables XXV to XXVI summarize the returns on a strategy that takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of them.

The results for portfolio holding periods between one month and one year are contained in Table XXV and are close to those obtained from the individual signals. Average returns, Sharpe ratios, as well as all CAPM-, Fama-French and Carhart-alphas are statistically significant and of large magnitudes. Carhart-alphas vary between 1.01% per month at the one-month and 0.5% at the one-year holding horizon. Furthermore, the difference in Sharpe ratios between the unconditional and the equal-weighted signal-based strategy is significant at the 10% level for all portfolio holding horizons.[37]

Within subgroups of stocks formed according to market capitalization, book-to-market value and industrial production beta, the equal-weighted strategy across all three signals consistently yields positive returns that are superior to those on the unconditional long-short strategy (which are even negative in some cases, see Table XXVI). The Carhart-alphas are large and significant in all market capitalization terciles, among low book-to-market companies and among stocks that have a medium or high sensitivity to industrial production shocks.

In Figure 2, the cumulative log-returns on the strategy that takes equal-weighted positions in all three signal-based long-short portfolios, as well as on the three presented signal-based strategies are plotted against the cumulative log-returns on the unconditional zero-investment strategy. The plot is for a portfolio holding horizon equal to one month and illustrates the superior performance of the signal-based strategies, which are able to avoid the dramatic drawdown that the unconditional strategy experiences since around 2003, when inflation seems to enter a procyclical regime in the UK.

As for the U.S., these results provide evidence in favor of the hypothesized relation between (inflation) risk premiums on individual equities and the cyclicality of inflation and indicate that the three signals are able to properly differentiate between pro- and countercyclical inflation states. Altogether, the evidence provided in this article suggests that inflation risk seems to be an important component of risk premiums in the cross-section of individual U.S. and UK equities that cannot be explained by widely accepted risk factors and that is closely related to whether inflation is pro- or countercyclical. These findings are of practical importance and highly relevant for individual, as well as institutional investors such as e.g. pension funds who want to preserve their capital in real terms.

[37]Two-sided p-values for the $H0$ of equal Sharpe Ratios are 0.098, 0.042, 0.037, 0.070 and 0.084 for the 1-, 3-, 6-, 9- and 12-month portfolio holding horizons. To test for equality of Sharpe ratios I use the heteroskedasticity and autocorrelation robust test statistic, as on p.$851-852$ in Ledoit and Wolf (2008), employing the Newey and West (1994) method.

5 Conclusion

I empirically show that the market price of inflation risk and hence inflation risk premiums in the cross-section of individual equities in the U.S. and the UK are time-varying and closely related to the cyclical nature of inflation. I find that the market price of inflation shocks is positive (negative) when inflation is procyclical (countercyclical). When inflation is countercyclical, positive inflation shocks are thus suggestive of bad economic times. Stocks exhibiting positive (negative) inflation-betas yield high (low) real returns during inflationary times, implying that their returns are countercyclical (procyclical) and consequently subject to negative (positive) inflation risk premiums on average. If the economy is in a procyclical inflation regime on the other hand, positive inflation shocks indicate good economic times and stocks exhibiting positive (negative) inflation-betas yield high (low) returns during inflationary times, are thus procyclical (countercyclical) and subject to positive (negative) inflation risk premiums.

It follows that a zero-investment strategy that is long the stocks with the lowest (highest) and short those with the highest (lowest) inflation-betas when inflation is countercyclical (procyclical) is expected to yield positive excess returns on average. Employing three alternative out-of-sample signals to determine whether inflation is pro- or countercyclical, I implement and test this zero-investment strategy over different time periods and contrast it with a strategy that is always long low and short high inflation-beta stocks. In the U.S. and the UK, the three signals are able to anticipate switches in the cyclicality of inflation in due time, such that the signal-based inflation-beta strategies yield statistically highly significant and economically large return premiums over both, pro- and countercyclical inflation periods, even after controlling for well-known risk factors.

REFERENCES

Ang, Andrew, Marie Brière, and Ombretta Signori, 2012, Inflation and individual equities, NBER Working Paper Series, Working Paper 17798.

Bekaert, Geert, and Xiaozheng Wang, 2010, Inflation risk and the inflation risk premium, *Economic Policy* 25, 755–806.

Boons, Martijn, Frans de Roon, and Marta Szymanowska, 2012, Sorting out inflation, Working Paper, SSRN.

Boudoukh, J., and M. Richardson, 1993, Stock returns and inflation: A long-horizon perspective, *American Economic Review* 83, 1346–1355.

Burkhardt, Dominic, and Henrik Hasseltoft, 2012, Understanding asset correlations, Working Paper, Swiss Finance Institute Research Paper No.12-38.

Duarte, Fernando M., 2013, Inflation risk and the cross section of stock returns, Federal Reserve Bank of New York Staff Reports, No.621.

Fama, E.F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

——— , and J.D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Fama, E.F., and G.W. Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115–146.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fisher, Irving, 1930, The theory of interest, *New York: MacMillan.*

Gregory, A., R. Thayaran, and A. Christidis, 2013, Constructing and testing alternative versions of the fama–french and carhart models in the uk, *Journal of Business Finance and Accounting* 40, 172–214.

Gultekin, N.B., 1983, Stock market returns and inflation: Evidence from other countries, *Journal of Finance* 38, 49–65.

Jaffe, J.F., and G. Mandelker, 1976, The "fisher effect" for risky assets: An empirical investigation, *Journal of Finance* 31, 447–458.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65—-91.

Katzur, Tomek, and Laura Spierdijk, 2010, Stock returns and inflation risk, Netspar Discussion Papers, No.11/2010-051.

Ledoit, O., and M. Wolf, 2008, Robust performance hypothesis testing with the sharpe ratio, *Journal of Empirical Finance* 15, 850–859.

Moerman, Gerard, and Mathijs van Dijk, 2010, Inflation risk and international asset returns, *Journal of Banking and Finance* 34, 840–855.

Nelson, C.R., 1976, Inflation and rates of return on common stocks, *Journal of Finance* 31, 471–483.

Newey, W.K., and K.D. West, 1994, Automatic lag selection in covariance matrix estimation, *Review of Economic Studies* 61, 631–653.

Schmeling, Maik, and Andreas Schrimpf, 2010, Expected inflation, expected stock returns, and money illusion: What can we learn from survey expectations, Working Paper SSRN.

Solnik, B., 1983, The relation between stock prices and inflationary expectations: The international evidence, *Journal of International Financial Markets, Institutions and Money* 7, 289–301.

——— , and V. Solnik, 1997, A multi-country test of the fisher model for stock returns, *Journal of Finance* 31, 471–483.

Vasicek, O.A., 1973, A note on using cross-sectional information in bayesian estimation of security betas, *Journal of Finance* 28, 1233–1239.

6 Tables and Figures

6.1 USA - 1965-2013

6.1.1 Summary Statistics

Table I. Summary Statistics for Inflation-Beta Portfolios, USA $1965-2013$**.** This Table reports summary statistics on 10 inflation-beta portfolios. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The portfolios are rebalanced monthly. **Column two** reports the average inflation-betas for the stocks in each of the ten portfolios. **Column three** (**Column four**) reports the average returns (standard deviations) on the ten portfolios. **Column five** and **Column six** contain the average number of stocks in each of the ten portfolios and the average portfolio turnover, respectively.

Inflation Portfolios 1965-2013 - Summary Statistics

Portfolios	**Average Inflation-β**	**Average Return**	**STD**	**Average # Stocks**	**Average Turnover**
1	-11.59	1.19	6.99	281.93	0.19
2	-6.78	1.14	5.94	281.99	0.35
3	-5.01	1.07	5.37	281.93	0.44
4	-3.79	0.96	4.92	281.99	0.49
5	-2.82	0.92	4.74	281.73	0.51
6	-2.00	0.77	4.62	282.23	0.51
7	-1.17	0.89	4.95	281.90	0.48
8	-0.17	0.84	4.94	282.03	0.44
9	1.37	0.80	5.38	281.89	0.35
10	6.30	0.71	7.35	282.03	0.19
Spread 1 - 10	*-17.89*	*0.48*	*-0.36*		

6.1.2 Fama and MacBeth (1973) Regressions

Table II. Fama and MacBeth (1973) Regression Results, USA $1965-2013$. This Table reports the results of a cross-sectional Fama and MacBeth (1973) regression over the entire sample period, and for the pro- and countercyclical inflation states separately. Employing the inflation-betas estimated in equation (1), I run a cross-sectional regression every month t of the excess returns ($R^e_{n,t} = R_{n,t} - R^f_t$) on the n stocks that are in the universe of investable stocks in month t onto a constant and their time t inflation-betas ($\hat{\beta}_{n,t}$) from equation (1) : $R^e_{n,t} = \gamma_t + \lambda_t \hat{\beta}_{n,t} + \varepsilon_t,\ n = 1, ..., N$. To get an estimate of the market price of inflation risk for pro-/countercyclical inflation states separately, I run the Fama and MacBeth (1973) regression by only considering the months t for which the signal indicates pro-/countercyclical inflation states. The resulting estimates $\hat{\gamma}_t$ and $\hat{\lambda}_t$ are averaged over time ($\overline{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t$ and $\overline{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t$). Two-sided p-Values are reported in parentheses.

Fama-MacBeth Cross Sectional Regressions: U.S. 1965-2013						
Signal	**Entire Sample**		**Countercyclical**		**Procyclical**	
	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$
Δ Real GDP - Inflation	0.0066	-0.0001	0.0055	-0.0003	0.0103	0.0007
	(0.0018)	(0.4283)	(0.0252)	(0.0128)	(0.0157)	(0.0130)
Δ Ind. Prod. - Inflation	0.0066	-0.0001	0.0063	-0.0003	0.0076	0.0005
	(0.0018)	(0.4283)	(0.0085)	(0.0266)	(0.0963)	(0.0487)
Stock - Bond	0.0066	-0.0001	0.0086	-0.0005	0.0046	0.0003
	(0.0018)	(0.4283)	(0.0023)	(0.0049)	(0.1454)	(0.1111)

6.1.3 Signal: Real GDP Growth - Inflation Correlations

Table III. Returns on Inflation-Beta Based Strategies I, USA $1965 - 2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0045	0.0032	0.0019	0.0084	0.0071	0.0073
	(0.1434)	(0.2601)	(0.5042)	(0.0060)	(0.0106)	(0.0075)
Market-rf	0.0514	0.0307	0.0575	0.2423	0.2109	0.2081
	(0.6517)	(0.7404)	(0.4725)	(0.0236)	(0.0082)	(0.0022)
SMB		0.2712	0.2702		0.2917	0.2918
		(0.0733)	(0.0997)		(0.0580)	(0.0553)
HML		0.1909	0.2365		0.1590	0.1542
		(0.3518)	(0.2502)		(0.4615)	(0.4922)
MOM			0.1441			-0.0151
			(0.3741)			(0.9245)
OBS	575	575	575	575	575	575
adj.R^2	-0.0003	0.0178	0.0259	0.0309	0.0504	0.0488
Panel 2: Alphas for Long-Leg						
Alpha	0.0018	0.0012	0.0004	0.0037	0.0031	0.0031
	(0.2834)	(0.3919)	(0.7710)	(0.0372)	(0.0311)	(0.0547)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0027	-0.0020	-0.0015	-0.0047	-0.0040	-0.0042
	(0.2001)	(0.3122)	(0.4468)	(0.0204)	(0.0359)	(0.0123)

Table IV. Returns on Inflation-Beta Based Strategies II, USA 1965 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0048	0.0044	0.0041	0.0043	0.0043	0.0094	0.0091	0.0086	0.0081	0.0077
	(0.0657)	(0.0837)	(0.0915)	(0.0701)	(0.0641)	(0.0003)	(0.0003)	(0.0005)	(0.0006)	(0.0009)
CAPM Alphas	0.0045	0.0041	0.0038	0.0039	0.0037	0.0084	0.0081	0.0074	0.0069	0.0064
	(0.1434)	(0.1708)	(0.1906)	(0.1629)	(0.1613)	(0.0060)	(0.0062)	(0.0095)	(0.0118)	(0.0151)
FF Alphas	0.0032	0.0030	0.0028	0.0030	0.0030	0.0071	0.0070	0.0066	0.0064	0.0062
	(0.2601)	(0.2806)	(0.3001)	(0.2554)	(0.2380)	(0.0106)	(0.0093)	(0.0125)	(0.0127)	(0.0133)
Carhart Alphas	0.0019	0.0015	0.0011	0.0014	0.0015	0.0073	0.0068	0.0060	0.0055	0.0052
	(0.5042)	(0.5941)	(0.6650)	(0.5816)	(0.5481)	(0.0075)	(0.0097)	(0.0215)	(0.0315)	(0.0387)
Sharpe Ratio	0.27	0.25	0.24	0.26	0.27	0.53	0.53	0.51	0.50	0.48
	(0.1009)	(0.1221)	(0.1275)	(0.0988)	(0.0914)	(0.0006)	(0.0005)	(0.0009)	(0.0013)	(0.0020)

Table V. Double-Sort Returns on Inflation-Beta Based Strategies, USA $1965-2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	0.0021	0.0031	0.0035	0.0051	0.0073	0.0074
	(0.2949)	(0.1544)	(0.1245)	(0.0105)	(0.0008)	(0.0011)
CAPM Alphas	0.0021	0.0031	0.0033	0.0046	0.0066	0.0066
	(0.3581)	(0.2626)	(0.2273)	(0.0440)	(0.0161)	(0.0147)
FF Alphas	0.0007	0.0019	0.0029	0.0029	0.0052	0.0064
	(0.6970)	(0.4442)	(0.2557)	(0.1576)	(0.0410)	(0.0097)
Carhart Alphas	-0.0009	0.0009	0.0016	0.0027	0.0062	0.0062
	(0.6705)	(0.7051)	(0.5117)	(0.2727)	(0.0115)	(0.0102)
Sharpe Ratio	0.1515	0.2060	0.2222	0.3709	0.4862	0.4747
	(0.3221)	(0.2343)	(0.1679)	(0.0102)	(0.0034)	(0.0017)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0073	0.0011	0.0002	0.0092	0.0044	0.0101
	(0.0110)	(0.6638)	(0.9398)	(0.0014)	(0.0766)	(0.0005)
CAPM Alphas	0.0072	0.0008	-0.0002	0.0082	0.0032	0.0095
	(0.0180)	(0.7703)	(0.9661)	(0.0070)	(0.2211)	(0.0082)
FF Alphas	0.0054	-0.0006	-0.0025	0.0066	0.0017	0.0074
	(0.0653)	(0.8182)	(0.4587)	(0.0245)	(0.5037)	(0.0335)
Carhart Alphas	0.0037	-0.0020	-0.0050	0.0056	0.0020	0.0076
	(0.1973)	(0.4487)	(0.1447)	(0.0549)	(0.4710)	(0.0391)
Sharpe Ratio	0.3687	0.0628	0.0109	0.4644	0.2563	0.5044
	(0.0106)	(0.6667)	(0.9500)	(0.0013)	(0.0855)	(0.0012)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0039	0.0035	0.0051	0.0079	0.0080	0.0068
	(0.1418)	(0.1699)	(0.0745)	(0.0031)	(0.0017)	(0.0166)
CAPM Alphas	0.0040	0.0033	0.0047	0.0072	0.0071	0.0062
	(0.2050)	(0.2660)	(0.1354)	(0.0219)	(0.0163)	(0.0454)
FF Alphas	0.0023	0.0029	0.0032	0.0061	0.0066	0.0048
	(0.4356)	(0.2861)	(0.3057)	(0.0417)	(0.0179)	(0.1039)
Carhart Alphas	0.0006	0.0017	0.0019	0.0062	0.0071	0.0039
	(0.8258)	(0.5432)	(0.5149)	(0.0385)	(0.0110)	(0.1625)
Sharpe Ratio	0.2125	0.1986	0.2581	0.4297	0.4551	0.3471
	(0.1919)	(0.2079)	(0.0881)	(0.0081)	(0.0029)	(0.0194)

6.1.4 Signal: Industrial Production Growth - Inflation Correlations

Table VI. Returns on Inflation-Beta Based Strategies I, USA $1965-2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0045	0.0032	0.0019	0.0078	0.0069	0.0076
	(0.1434)	(0.2601)	(0.5042)	(0.0055)	(0.0086)	(0.0034)
Market-rf	0.0514	0.0307	0.0575	0.2114	0.2104	0.1967
	(0.6517)	(0.7404)	(0.4725)	(0.0473)	(0.0085)	(0.0053)
SMB		0.2712	0.2702		0.1388	0.1393
		(0.0733)	(0.0997)		(0.3256)	(0.3022)
HML		0.1909	0.2365		0.1457	0.1225
		(0.3518)	(0.2502)		(0.4903)	(0.5903)
MOM			0.1441			-0.0736
			(0.3741)			(0.6372)
OBS	575	575	575	575	575	575
adj.R^2	-0.0003	0.0178	0.0259	0.0231	0.0274	0.0282
Panel 2: Alphas for Long-Leg						
Alpha	0.0018	0.0012	0.0004	0.0034	0.0030	0.0032
	(0.2834)	(0.3919)	(0.7710)	(0.0427)	(0.0328)	(0.0364)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0027	-0.0020	-0.0015	-0.0044	-0.0039	-0.0043
	(0.2001)	(0.3122)	(0.4468)	(0.0222)	(0.0327)	(0.0076)

Table VII. Returns on Inflation-Beta Based Strategies II, USA $1965-2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k=1,3,6,9,12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0048	0.0044	0.0041	0.0043	0.0043	0.0087	0.0085	0.0079	0.0074	0.0069
	(0.0657)	(0.0837)	(0.0915)	(0.0701)	(0.0641)	(0.0007)	(0.0007)	(0.0012)	(0.0018)	(0.0028)
CAPM Alphas	0.0045	0.0041	0.0038	0.0039	0.0037	0.0078	0.0076	0.0069	0.0063	0.0058
	(0.1434)	(0.1708)	(0.1906)	(0.1629)	(0.1613)	(0.0055)	(0.0056)	(0.0085)	(0.0114)	(0.0166)
FF Alphas	0.0032	0.0030	0.0028	0.0030	0.0030	0.0069	0.0068	0.0064	0.0061	0.0058
	(0.2601)	(0.2806)	(0.3001)	(0.2554)	(0.2380)	(0.0086)	(0.0069)	(0.0091)	(0.0092)	(0.0111)
Carhart Alphas	0.0019	0.0015	0.0011	0.0014	0.0015	0.0076	0.0072	0.0063	0.0056	0.0052
	(0.5042)	(0.5941)	(0.6650)	(0.5816)	(0.5481)	(0.0034)	(0.0045)	(0.0109)	(0.0165)	(0.0236)
Sharpe Ratio	0.27	0.25	0.24	0.26	0.27	0.49	0.49	0.47	0.45	0.43
	(0.1009)	(0.1221)	(0.1275)	(0.0988)	(0.0914)	(0.0007)	(0.0007)	(0.0012)	(0.0020)	(0.0034)

Table VIII. Double-Sort Returns on Inflation-Beta Based Strategies, USA 1965 – 2013. This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	0.0021	0.0031	0.0035	0.0051	0.0067	0.0070
	(0.2949)	(0.1544)	(0.1245)	(0.0105)	(0.0022)	(0.0021)
CAPM Alphas	0.0021	0.0031	0.0033	0.0045	0.0060	0.0062
	(0.3581)	(0.2626)	(0.2273)	(0.0357)	(0.0177)	(0.0148)
FF Alphas	0.0007	0.0019	0.0029	0.0027	0.0042	0.0062
	(0.6970)	(0.4442)	(0.2557)	(0.1449)	(0.0635)	(0.0090)
Carhart Alphas	-0.0009	0.0009	0.0016	0.0029	0.0056	0.0067
	(0.6705)	(0.7051)	(0.5117)	(0.1999)	(0.0117)	(0.0045)
Sharpe Ratio	0.1515	0.2060	0.2222	0.3710	0.4443	0.4466
	(0.3221)	(0.2343)	(0.1679)	(0.0074)	(0.0042)	(0.0022)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0073	0.0011	0.0002	0.0083	0.0025	0.0076
	(0.0110)	(0.6638)	(0.9398)	(0.0040)	(0.3181)	(0.0097)
CAPM Alphas	0.0072	0.0008	-0.0002	0.0077	0.0012	0.0067
	(0.0180)	(0.7703)	(0.9661)	(0.0083)	(0.6187)	(0.0448)
FF Alphas	0.0054	-0.0006	-0.0025	0.0066	-0.0002	0.0050
	(0.0653)	(0.8182)	(0.4587)	(0.0226)	(0.9401)	(0.1256)
Carhart Alphas	0.0037	-0.0020	-0.0050	0.0061	0.0007	0.0057
	(0.1973)	(0.4487)	(0.1447)	(0.0334)	(0.7701)	(0.1091)
Sharpe Ratio	0.3687	0.0628	0.0109	0.4171	0.1444	0.3747
	(0.0106)	(0.6667)	(0.9500)	(0.0026)	(0.3041)	(0.0132)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0039	0.0035	0.0051	0.0064	0.0069	0.0065
	(0.1418)	(0.1699)	(0.0745)	(0.0169)	(0.0070)	(0.0225)
CAPM Alphas	0.0040	0.0033	0.0047	0.0058	0.0060	0.0060
	(0.2050)	(0.2660)	(0.1354)	(0.0510)	(0.0318)	(0.0479)
FF Alphas	0.0023	0.0029	0.0032	0.0048	0.0054	0.0051
	(0.4356)	(0.2861)	(0.3057)	(0.0908)	(0.0392)	(0.0968)
Carhart Alphas	0.0006	0.0017	0.0019	0.0052	0.0065	0.0049
	(0.8258)	(0.5432)	(0.5149)	(0.0599)	(0.0118)	(0.0963)
Sharpe Ratio	0.2125	0.1986	0.2581	0.3462	0.3908	0.3306
	(0.1919)	(0.2079)	(0.0881)	(0.0256)	(0.0073)	(0.0229)

6.1.5 Signal: Stock - Bond Correlations

Table IX. Returns on Inflation-Beta Based Strategies I, USA 1965 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0045	0.0032	0.0019	0.0102	0.0084	0.0077
	(0.1434)	(0.2601)	(0.5042)	(0.0006)	(0.0031)	(0.0101)
Market-rf	0.0514	0.0307	0.0575	-0.0037	0.0781	0.0918
	(0.6517)	(0.7404)	(0.4725)	(0.9730)	(0.3452)	(0.2409)
SMB		0.2712	0.2702		-0.0140	-0.0145
		(0.0733)	(0.0997)		(0.9078)	(0.9049)
HML		0.1909	0.2365		0.3982	0.4214
		(0.3518)	(0.2502)		(0.0206)	(0.0204)
MOM			0.1441			0.0736
			(0.3741)			(0.6185)
OBS	575	575	575	575	575	575
adj.R^2	-0.0003	0.0178	0.0259	-0.0017	0.0283	0.0292
Panel 2: Alphas for Long-Leg						
Alpha	0.0018	0.0012	0.0004	0.0046	0.0038	0.0033
	(0.2834)	(0.3919)	(0.7710)	(0.0100)	(0.0253)	(0.0754)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0027	-0.0020	-0.0015	-0.0056	-0.0046	-0.0044
	(0.2001)	(0.3122)	(0.4468)	(0.0038)	(0.0078)	(0.0074)

Table X. Returns on Inflation-Beta Based Strategies II, USA $1965-2013$. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0048	0.0044	0.0041	0.0043	0.0043	0.0102	0.0103	0.0099	0.0095	0.0092
	(0.0657)	(0.0837)	(0.0915)	(0.0701)	(0.0641)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
CAPM Alphas	0.0045	0.0041	0.0038	0.0039	0.0037	0.0102	0.0103	0.0099	0.0094	0.0090
	(0.1434)	(0.1708)	(0.1906)	(0.1629)	(0.1613)	(0.0006)	(0.0004)	(0.0004)	(0.0005)	(0.0006)
FF Alphas	0.0032	0.0030	0.0028	0.0030	0.0030	0.0084	0.0086	0.0085	0.0082	0.0081
	(0.2601)	(0.2806)	(0.3001)	(0.2554)	(0.2380)	(0.0031)	(0.0018)	(0.0017)	(0.0018)	(0.0018)
Carhart Alphas	0.0019	0.0015	0.0011	0.0014	0.0015	0.0077	0.0078	0.0074	0.0068	0.0067
	(0.5042)	(0.5941)	(0.6650)	(0.5816)	(0.5481)	(0.0101)	(0.0082)	(0.0098)	(0.0125)	(0.0128)
Sharpe Ratio	0.27	0.25	0.24	0.26	0.27	0.58	0.60	0.59	0.58	0.58
	(0.1009)	(0.1221)	(0.1275)	(0.0988)	(0.0914)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)

Table XI. Double-Sort Returns on Inflation-Beta Based Strategies, USA 1965 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	0.0021	0.0031	0.0035	0.0048	0.0069	0.0079
	(0.2949)	(0.1544)	(0.1245)	(0.0163)	(0.0015)	(0.0005)
CAPM Alphas	0.0021	0.0031	0.0033	0.0046	0.0068	0.0079
	(0.3581)	(0.2626)	(0.2273)	(0.0372)	(0.0110)	(0.0031)
FF Alphas	0.0007	0.0019	0.0029	0.0022	0.0047	0.0066
	(0.6970)	(0.4442)	(0.2557)	(0.2524)	(0.0585)	(0.0106)
Carhart Alphas	-0.0009	0.0009	0.0016	0.0015	0.0051	0.0062
	(0.6705)	(0.7051)	(0.5117)	(0.5192)	(0.0439)	(0.0226)
Sharpe Ratio	0.1515	0.2060	0.2222	0.3479	0.4602	0.5035
	(0.3221)	(0.2343)	(0.1679)	(0.0141)	(0.0043)	(0.0006)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0073	0.0011	0.0002	0.0078	0.0070	0.0098
	(0.0110)	(0.6638)	(0.9398)	(0.0069)	(0.0050)	(0.0008)
CAPM Alphas	0.0072	0.0008	-0.0002	0.0079	0.0069	0.0099
	(0.0180)	(0.7703)	(0.9661)	(0.0105)	(0.0060)	(0.0048)
FF Alphas	0.0054	-0.0006	-0.0025	0.0060	0.0053	0.0082
	(0.0653)	(0.8182)	(0.4587)	(0.0483)	(0.0325)	(0.0185)
Carhart Alphas	0.0037	-0.0020	-0.0050	0.0044	0.0043	0.0076
	(0.1973)	(0.4487)	(0.1447)	(0.1662)	(0.1415)	(0.0534)
Sharpe Ratio	0.3687	0.0628	0.0109	0.3917	0.4075	0.4879
	(0.0106)	(0.6667)	(0.9500)	(0.0063)	(0.0033)	(0.0017)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0039	0.0035	0.0051	0.0081	0.0068	0.0092
	(0.1418)	(0.1699)	(0.0745)	(0.0022)	(0.0077)	(0.0013)
CAPM Alphas	0.0040	0.0033	0.0047	0.0085	0.0068	0.0096
	(0.2050)	(0.2660)	(0.1354)	(0.0056)	(0.0173)	(0.0015)
FF Alphas	0.0023	0.0029	0.0032	0.0064	0.0050	0.0084
	(0.4356)	(0.2861)	(0.3057)	(0.0260)	(0.0686)	(0.0072)
Carhart Alphas	0.0006	0.0017	0.0019	0.0057	0.0049	0.0064
	(0.8258)	(0.5432)	(0.5149)	(0.0544)	(0.0987)	(0.0503)
Sharpe Ratio	0.2125	0.1986	0.2581	0.4452	0.3864	0.4677
	(0.1919)	(0.2079)	(0.0881)	(0.0047)	(0.0097)	(0.0016)

6.1.6 Equal-Weighted Across All Signals

Table XII. Equal-Weighted Portfolio across Signals, USA $1965 - 2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **Equal weighted portfolio across all signal-based strategies** takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of the respective signal-based long-short strategies. The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0048	0.0044	0.0041	0.0043	0.0043	0.0094	0.0093	0.0088	0.0083	0.0079
	(0.0657)	(0.0837)	(0.0915)	(0.0701)	(0.0641)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
CAPM Alphas	0.0045	0.0041	0.0038	0.0039	0.0037	0.0088	0.0086	0.0080	0.0075	0.0071
	(0.1434)	(0.1708)	(0.1906)	(0.1629)	(0.1613)	(0.0008)	(0.0007)	(0.0009)	(0.0012)	(0.0015)
FF Alphas	0.0032	0.0030	0.0028	0.0030	0.0030	0.0075	0.0074	0.0071	0.0069	0.0067
	(0.2601)	(0.2806)	(0.3001)	(0.2554)	(0.2380)	(0.0019)	(0.0013)	(0.0015)	(0.0016)	(0.0016)
Carhart Alphas	0.0019	0.0015	0.0011	0.0014	0.0015	0.0075	0.0073	0.0066	0.0060	0.0057
	(0.5042)	(0.5941)	(0.6650)	(0.5816)	(0.5481)	(0.0023)	(0.0025)	(0.0053)	(0.0078)	(0.0094)
Sharpe Ratio	0.27	0.25	0.24	0.26	0.27	0.61	0.62	0.60	0.59	0.58
	(0.1009)	(0.1221)	(0.1275)	(0.0988)	(0.0914)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)

Table XIII. Double-Sort Returns on Equal-Weighted Portfolio across Signals, USA 1965−2013. This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **Equal weighted portfolio across all signal-based strategies** takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of the respective signal-based long-short strategies. The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	0.0021	0.0031	0.0035	0.0051	0.0067	0.0074
	(0.2949)	(0.1544)	(0.1245)	(0.0105)	(0.0022)	(0.0002)
CAPM Alphas	0.0021	0.0031	0.0033	0.0045	0.0060	0.0069
	(0.3581)	(0.2626)	(0.2273)	(0.0357)	(0.0177)	(0.0037)
FF Alphas	0.0007	0.0019	0.0029	0.0027	0.0042	0.0064
	(0.6970)	(0.4442)	(0.2557)	(0.1449)	(0.0635)	(0.0034)
Carhart Alphas	-0.0009	0.0009	0.0016	0.0029	0.0056	0.0063
	(0.6705)	(0.7051)	(0.5117)	(0.1999)	(0.0117)	(0.0039)
Sharpe Ratio	0.1515	0.2060	0.2222	0.3710	0.4443	0.5395
	(0.3221)	(0.2343)	(0.1679)	(0.0074)	(0.0042)	(0.0001)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0073	0.0011	0.0002	0.0083	0.0025	0.0092
	(0.0110)	(0.6638)	(0.9398)	(0.0040)	(0.3181)	(0.0002)
CAPM Alphas	0.0072	0.0008	-0.0002	0.0077	0.0012	0.0087
	(0.0180)	(0.7703)	(0.9661)	(0.0083)	(0.6187)	(0.0047)
FF Alphas	0.0054	-0.0006	-0.0025	0.0066	-0.0002	0.0068
	(0.0653)	(0.8182)	(0.4587)	(0.0226)	(0.9401)	(0.0233)
Carhart Alphas	0.0037	-0.0020	-0.0050	0.0061	0.0007	0.0070
	(0.1973)	(0.4487)	(0.1447)	(0.0334)	(0.7701)	(0.0407)
Sharpe Ratio	0.3687	0.0628	0.0109	0.4171	0.1444	0.5339
	(0.0106)	(0.6667)	(0.9500)	(0.0026)	(0.3041)	(0.0003)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0039	0.0035	0.0051	0.0064	0.0069	0.0075
	(0.1418)	(0.1699)	(0.0745)	(0.0169)	(0.0070)	(0.0027)
CAPM Alphas	0.0040	0.0033	0.0047	0.0058	0.0060	0.0072
	(0.2050)	(0.2660)	(0.1354)	(0.0510)	(0.0318)	(0.0071)
FF Alphas	0.0023	0.0029	0.0032	0.0048	0.0054	0.0061
	(0.4356)	(0.2861)	(0.3057)	(0.0908)	(0.0392)	(0.0214)
Carhart Alphas	0.0006	0.0017	0.0019	0.0052	0.0065	0.0051
	(0.8258)	(0.5432)	(0.5149)	(0.0599)	(0.0118)	(0.0483)
Sharpe Ratio	0.2125	0.1986	0.2581	0.3462	0.3908	0.4357
	(0.1919)	(0.2079)	(0.0881)	(0.0256)	(0.0073)	(0.0026)

6.1.7 Cumulative Log-Returns

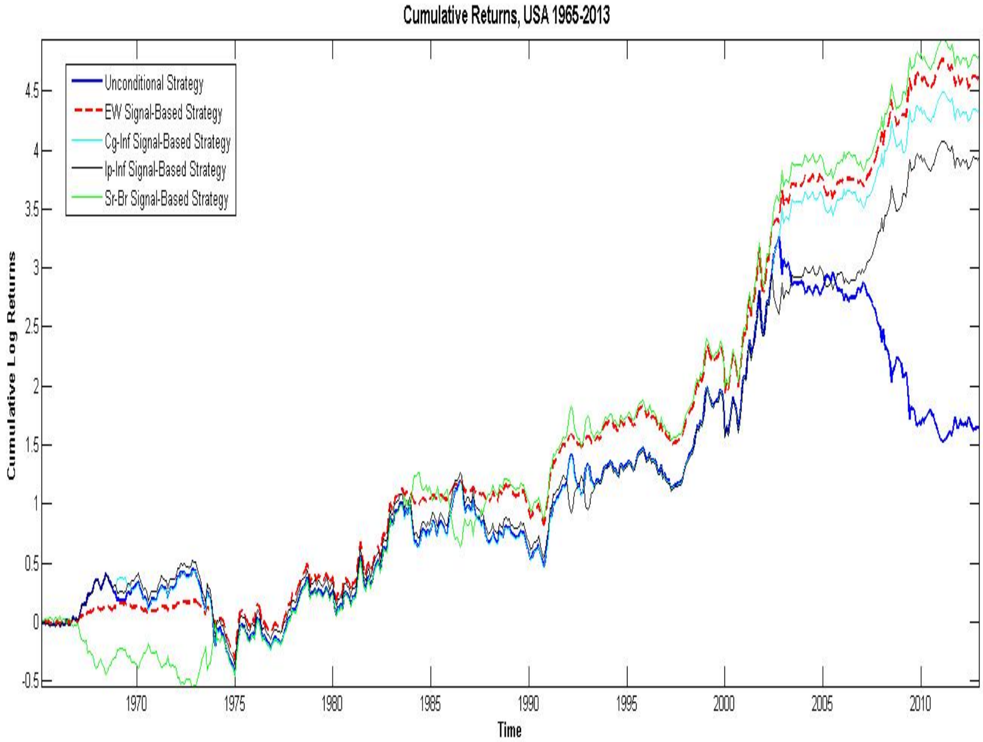


Figure 1. Cumulative Log-Returns on the Equal-Weighted Portfolio across the three Signal-Based Long-Short Strategies and on the three Signal-Based Long-Short Strategies versus the Cumulative Log-Returns on the Unconditional Inflation Beta Strategy.

6.2 UK - 1980-2013

6.2.1 Summary Statistics

Table XIV. Summary Statistics for Inflation-Beta Portfolios, UK $1980 - 2013$**.** This Table reports summary statistics on 10 inflation-beta portfolios. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The portfolios are rebalanced monthly. **Column two** reports the average inflation-betas for the stocks in each of the ten portfolios. **Column three** (**Column four**) reports the average returns (standard deviations) on the ten portfolios. **Column five** and **Column six** contain the average number of stocks in each of the ten portfolios and the average portfolio turnover, respectively.

Inflation Portfolios UK 1980-2013 - Summary Statistics					
Portfolios	**Average Inflation-β**	**Average Return**	**STD**	**Average # Stocks**	**Average Turnover**
1	-6.54	0.90	6.28	115.93	0.16
2	-2.73	1.15	6.08	116.02	0.30
3	-1.73	1.34	5.12	115.94	0.40
4	-1.14	1.05	5.18	116.05	0.45
5	-0.68	0.98	4.68	115.72	0.48
6	-0.25	0.99	5.08	116.22	0.48
7	0.21	0.94	4.79	115.94	0.46
8	0.82	1.17	5.21	116.05	0.40
9	1.85	1.03	5.91	115.91	0.31
10	5.77	0.79	6.86	116.03	0.17
Spread 1 - 10	*-12.31*	*0.11*	*-0.57*		

6.2.2 Fama and MacBeth (1973) Regressions

Table XV. Fama and MacBeth (1973) Regression Results, UK $1980-2013$**.** This Table reports the results of a cross-sectional Fama and MacBeth (1973) regression over the entire sample period, and for the pro- and countercyclical inflation states separately. Employing the inflation-betas estimated in equation (1), I run a cross-sectional regression every month t of the excess returns ($R^e_{n,t} = R_{n,t} - R^f_t$) on the n stocks that are in the universe of investable stocks in month t onto a constant and their time t inflation-betas ($\hat{\beta}_{n,t}$) from equation (1) : $R^e_{n,t} = \gamma_t + \lambda_t \hat{\beta}_{n,t} + \varepsilon_t,\ n = 1, ..., N$. To get an estimate of the market price of inflation risk for pro-/countercyclical inflation states separately, I run the Fama and MacBeth (1973) regression by only considering the months t for which the signal indicates pro-/countercyclical inflation states. The resulting estimates $\hat{\gamma}_t$ and $\hat{\lambda}_t$ are averaged over time ($\overline{\gamma} = \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_t$ and $\overline{\lambda} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_t$). Two-sided p-Values are reported in parentheses.

Fama-MacBeth Cross Sectional Regressions: UK 1980-2013						
Signal	**Entire Sample**		**Countercyclical**		**Procyclical**	
	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$
Δ Real GDP - Inflation	0.0048	-0.0002	0.0051	-0.0003	0.0040	0.0003
	(0.0431)	(0.3051)	(0.0634)	(0.1081)	(0.3904)	(0.0587)
Δ Ind. Prod. - Inflation	0.0048	-0.0002	0.0048	-0.0003	0.0048	0.0003
	(0.0431)	(0.3051)	(0.0853)	(0.1084)	(0.2872)	(0.0617)
Stock - Bond	0.0048	-0.0002	0.0054	-0.0003	0.0031	0.0003
	(0.0431)	(0.3051)	(0.0468)	(0.1109)	(0.5146)	(0.0637)

6.2.3 Signal: Real GDP Growth - Inflation Correlations

Table XVI. Returns on Inflation-Beta Based Strategies I, UK 1980 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t + 1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0012	0.0021	0.0024	0.0063	0.0069	0.0101
	(0.7032)	(0.5126)	(0.5580)	(0.0434)	(0.0235)	(0.0032)
Market-rf	-0.0254	-0.0165	-0.0205	0.1164	0.1223	0.0867
	(0.7350)	(0.8228)	(0.7776)	(0.1227)	(0.1146)	(0.2503)
SMB		-0.0412	-0.0473		0.0474	-0.0083
		(0.8242)	(0.7821)		(0.8035)	(0.9572)
HML		-0.2488	-0.2712		-0.1713	-0.3734
		(0.1188)	(0.0860)		(0.2873)	(0.0122)
MOM			-0.0344			-0.3102
			(0.8517)			(0.0299)
OBS	387	387	387	387	387	387
adj.R^2	-0.0022	0.0124	0.0102	0.0060	0.0110	0.0426
Panel 2: Alphas for Long-Leg						
Alpha	-0.0018	-0.0016	-0.0013	0.0008	0.0008	0.0026
	(0.4206)	(0.4201)	(0.5786)	(0.7769)	(0.7317)	(0.3967)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0030	-0.0037	-0.0037	-0.0056	-0.0061	-0.0075
	(0.2407)	(0.1208)	(0.2668)	(0.0071)	(0.0022)	(0.0003)

Table XVII. Returns on Inflation-Beta Based Strategies II, UK 1980 − 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0011	0.0005	0.0000	0.0005	0.0007	0.0069	0.0076	0.0066	0.0052	0.0050
	(0.7086)	(0.8441)	(0.9898)	(0.8386)	(0.7814)	(0.0189)	(0.0064)	(0.0133)	(0.0430)	(0.0443)
CAPM Alphas	0.0012	0.0008	0.0002	0.0006	0.0006	0.0063	0.0070	0.0060	0.0047	0.0045
	(0.7032)	(0.7875)	(0.9354)	(0.8191)	(0.8263)	(0.0434)	(0.0149)	(0.0212)	(0.0524)	(0.0658)
FF Alphas	0.0021	0.0015	0.0009	0.0010	0.0009	0.0069	0.0076	0.0066	0.0052	0.0052
	(0.5126)	(0.6212)	(0.7537)	(0.6888)	(0.7162)	(0.0235)	(0.0080)	(0.0108)	(0.0308)	(0.0363)
Carhart Alphas	0.0024	0.0014	0.0004	0.0008	0.0007	0.0101	0.0099	0.0075	0.0055	0.0050
	(0.5580)	(0.7152)	(0.8949)	(0.7668)	(0.8044)	(0.0032)	(0.0021)	(0.0062)	(0.0288)	(0.0542)
Sharpe Ratio	0.07	0.03	0.00	0.04	0.05	0.42	0.48	0.44	0.36	0.36
	(0.7426)	(0.8639)	(0.9907)	(0.8425)	(0.7891)	(0.0209)	(0.0075)	(0.0134)	(0.0362)	(0.0416)

Table XVIII. Double-Sort Returns on Inflation-Beta Based Strategies, UK 1980 – 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	-0.0032	0.0021	0.0020	0.0053	0.0074	0.0034
	(0.2475)	(0.3824)	(0.4670)	(0.0582)	(0.0021)	(0.2110)
CAPM Alphas	-0.0038	0.0020	0.0017	0.0058	0.0073	0.0028
	(0.3478)	(0.5237)	(0.4984)	(0.1398)	(0.0129)	(0.2679)
FF Alphas	-0.0046	0.0014	0.0019	0.0054	0.0072	0.0026
	(0.2497)	(0.6542)	(0.4378)	(0.1751)	(0.0139)	(0.3097)
Carhart Alphas	-0.0060	-0.0005	0.0015	0.0077	0.0068	0.0059
	(0.1643)	(0.8835)	(0.6487)	(0.0633)	(0.0454)	(0.0278)
Sharpe Ratio	-0.2040	0.1540	0.1282	0.3345	0.5448	0.2206
	(0.4043)	(0.4819)	(0.4584)	(0.1550)	(0.0017)	(0.1760)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0018	0.0024	-0.0036	0.0082	0.0045	0.0027
	(0.5886)	(0.5438)	(0.4605)	(0.0132)	(0.2439)	(0.5799)
CAPM Alphas	0.0016	0.0023	-0.0044	0.0081	0.0034	0.0027
	(0.6866)	(0.6243)	(0.3683)	(0.0292)	(0.4711)	(0.5883)
FF Alphas	0.0016	0.0031	-0.0033	0.0081	0.0037	0.0045
	(0.6829)	(0.5265)	(0.5031)	(0.0358)	(0.4460)	(0.3435)
Carhart Alphas	0.0030	0.0024	-0.0065	0.0090	0.0047	0.0073
	(0.4805)	(0.6465)	(0.2433)	(0.0273)	(0.3425)	(0.1811)
Sharpe Ratio	0.0953	0.1070	-0.1301	0.4384	0.2055	0.0976
	(0.6418)	(0.6224)	(0.4704)	(0.0271)	(0.3338)	(0.5899)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0049	0.0011	0.0048	0.0066	0.0039	0.0111
	(0.2035)	(0.7494)	(0.1973)	(0.0852)	(0.2433)	(0.0030)
CAPM Alphas	0.0043	0.0006	0.0054	0.0064	0.0038	0.0119
	(0.3495)	(0.8794)	(0.1997)	(0.1575)	(0.2885)	(0.0023)
FF Alphas	0.0057	0.0001	0.0050	0.0074	0.0039	0.0119
	(0.2013)	(0.9704)	(0.2533)	(0.0942)	(0.2635)	(0.0031)
Carhart Alphas	0.0075	0.0027	0.0030	0.0057	0.0069	0.0131
	(0.0723)	(0.5158)	(0.5561)	(0.1936)	(0.0584)	(0.0052)
Sharpe Ratio	0.2243	0.0563	0.2274	0.3038	0.2058	0.5264
	(0.2976)	(0.7612)	(0.2555)	(0.1485)	(0.2511)	(0.0026)

6.2.4 Signal: Industrial Production Growth - Inflation Correlations

Table XIX. Returns on Inflation-Beta Based Strategies I, UK 1980 − 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0012	0.0021	0.0024	0.0067	0.0072	0.0105
	(0.7032)	(0.5126)	(0.5580)	(0.0337)	(0.0182)	(0.0022)
Market-rf	-0.0254	-0.0165	-0.0205	0.1118	0.1175	0.0812
	(0.7350)	(0.8228)	(0.7776)	(0.1363)	(0.1274)	(0.2788)
SMB		-0.0412	-0.0473		0.0403	-0.0163
		(0.8242)	(0.7821)		(0.8326)	(0.9152)
HML		-0.2488	-0.2712		-0.1649	-0.3706
		(0.1188)	(0.0860)		(0.3079)	(0.0133)
MOM			-0.0344			-0.3157
			(0.8517)			(0.0267)
OBS	387	387	387	387	387	387
adj.R^2	-0.0022	0.0124	0.0102	0.0053	0.0094	0.0423
Panel 2: Alphas for Long-Leg						
Alpha	-0.0018	-0.0016	-0.0013	0.0009	0.0009	0.0028
	(0.4206)	(0.4201)	(0.5786)	(0.7316)	(0.6830)	(0.3645)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0030	-0.0037	-0.0037	-0.0058	-0.0062	-0.0077
	(0.2407)	(0.1208)	(0.2668)	(0.0054)	(0.0017)	(0.0002)

Table XX. Returns on Inflation-Beta Based Strategies II, UK $1980-2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0011	0.0005	0.0000	0.0005	0.0007	0.0072	0.0079	0.0069	0.0056	0.0054
	(0.7086)	(0.8441)	(0.9898)	(0.8386)	(0.7814)	(0.0144)	(0.0046)	(0.0093)	(0.0299)	(0.0307)
CAPM Alphas	0.0012	0.0008	0.0002	0.0006	0.0006	0.0067	0.0073	0.0063	0.0050	0.0049
	(0.7032)	(0.7875)	(0.9354)	(0.8191)	(0.8263)	(0.0337)	(0.0109)	(0.0145)	(0.0352)	(0.0452)
FF Alphas	0.0021	0.0015	0.0009	0.0010	0.0009	0.0072	0.0079	0.0070	0.0056	0.0055
	(0.5126)	(0.6212)	(0.7537)	(0.6888)	(0.7162)	(0.0182)	(0.0060)	(0.0076)	(0.0211)	(0.0253)
Carhart Alphas	0.0024	0.0014	0.0004	0.0008	0.0007	0.0105	0.0102	0.0079	0.0059	0.0054
	(0.5580)	(0.7152)	(0.8949)	(0.7668)	(0.8044)	(0.0022)	(0.0015)	(0.0040)	(0.0194)	(0.0389)
Sharpe Ratio	0.07	0.03	0.00	0.04	0.05	0.43	0.50	0.46	0.38	0.38
	(0.7426)	(0.8639)	(0.9907)	(0.8425)	(0.7891)	(0.0157)	(0.0054)	(0.0093)	(0.0248)	(0.0289)

Table XXI. Double-Sort Returns on Inflation-Beta Based Strategies, UK 1980−2013. This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	-0.0032	0.0021	0.0020	0.0064	0.0073	0.0034
	(0.2475)	(0.3824)	(0.4670)	(0.0212)	(0.0024)	(0.1999)
CAPM Alphas	-0.0038	0.0020	0.0017	0.0068	0.0072	0.0029
	(0.3478)	(0.5237)	(0.4984)	(0.0836)	(0.0140)	(0.2515)
FF Alphas	-0.0046	0.0014	0.0019	0.0065	0.0071	0.0027
	(0.2497)	(0.6542)	(0.4378)	(0.1076)	(0.0157)	(0.2888)
Carhart Alphas	-0.0060	-0.0005	0.0015	0.0088	0.0067	0.0061
	(0.1643)	(0.8835)	(0.6487)	(0.0348)	(0.0505)	(0.0224)
Sharpe Ratio	-0.2040	0.1540	0.1282	0.4076	0.5378	0.2261
	(0.4043)	(0.4819)	(0.4584)	(0.0835)	(0.0018)	(0.1669)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0018	0.0024	-0.0036	0.0077	0.0048	0.0037
	(0.5886)	(0.5438)	(0.4605)	(0.0212)	(0.2161)	(0.4433)
CAPM Alphas	0.0016	0.0023	-0.0044	0.0076	0.0036	0.0038
	(0.6866)	(0.6243)	(0.3683)	(0.0419)	(0.4365)	(0.4564)
FF Alphas	0.0016	0.0031	-0.0033	0.0076	0.0039	0.0055
	(0.6829)	(0.5265)	(0.5031)	(0.0497)	(0.4141)	(0.2493)
Carhart Alphas	0.0030	0.0024	-0.0065	0.0085	0.0051	0.0085
	(0.4805)	(0.6465)	(0.2433)	(0.0375)	(0.3058)	(0.1231)
Sharpe Ratio	0.0953	0.1070	-0.1301	0.4074	0.2182	0.1351
	(0.6418)	(0.6224)	(0.4704)	(0.0398)	(0.3052)	(0.4549)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0049	0.0011	0.0048	0.0073	0.0044	0.0114
	(0.2035)	(0.7494)	(0.1973)	(0.0586)	(0.1847)	(0.0024)
CAPM Alphas	0.0043	0.0006	0.0054	0.0071	0.0044	0.0121
	(0.3495)	(0.8794)	(0.1997)	(0.1221)	(0.2229)	(0.0018)
FF Alphas	0.0057	0.0001	0.0050	0.0080	0.0044	0.0121
	(0.2013)	(0.9704)	(0.2533)	(0.0707)	(0.2006)	(0.0024)
Carhart Alphas	0.0075	0.0027	0.0030	0.0063	0.0073	0.0133
	(0.0723)	(0.5158)	(0.5561)	(0.1539)	(0.0460)	(0.0041)
Sharpe Ratio	0.2243	0.0563	0.2274	0.3341	0.2340	0.5385
	(0.2976)	(0.7612)	(0.2555)	(0.1147)	(0.1889)	(0.0020)

6.2.5 Signal: Stock - Bond Correlations

Table XXII. Returns on Inflation-Beta Based Strategies I, UK 1980 − 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0012	0.0021	0.0024	0.0062	0.0067	0.0099
	(0.7032)	(0.5126)	(0.5580)	(0.0498)	(0.0276)	(0.0041)
Market-rf	-0.0254	-0.0165	-0.0205	0.1170	0.1229	0.0878
	(0.7350)	(0.8228)	(0.7776)	(0.1209)	(0.1130)	(0.2442)
SMB		-0.0412	-0.0473		0.0511	-0.0036
		(0.8242)	(0.7821)		(0.7882)	(0.9812)
HML		-0.2488	-0.2712		-0.1708	-0.3696
		(0.1188)	(0.0860)		(0.2889)	(0.0133)
MOM			-0.0344			-0.3051
			(0.8517)			(0.0333)
OBS	387	387	387	387	387	387
adj.R^2	-0.0022	0.0124	0.0102	0.0061	0.0111	0.0416
Panel 2: Alphas for Long-Leg						
Alpha	-0.0018	-0.0016	-0.0013	0.0007	0.0007	0.0025
	(0.4206)	(0.4201)	(0.5786)	(0.8005)	(0.7594)	(0.4177)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0030	-0.0037	-0.0037	-0.0055	-0.0060	-0.0074
	(0.2407)	(0.1208)	(0.2668)	(0.0081)	(0.0027)	(0.0004)

Table XXIII. Returns on Inflation-Beta Based Strategies II, UK $1980 - 2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0011	0.0005	0.0000	0.0005	0.0007	0.0068	0.0074	0.0065	0.0050	0.0049
	(0.7086)	(0.8441)	(0.9898)	(0.8386)	(0.7814)	(0.0219)	(0.0077)	(0.0152)	(0.0489)	(0.0505)
CAPM Alphas	0.0012	0.0008	0.0002	0.0006	0.0006	0.0062	0.0068	0.0058	0.0045	0.0044
	(0.7032)	(0.7875)	(0.9354)	(0.8191)	(0.8263)	(0.0498)	(0.0178)	(0.0245)	(0.0608)	(0.0755)
FF Alphas	0.0021	0.0015	0.0009	0.0010	0.0009	0.0067	0.0074	0.0065	0.0051	0.0050
	(0.5126)	(0.6212)	(0.7537)	(0.6888)	(0.7162)	(0.0276)	(0.0098)	(0.0127)	(0.0362)	(0.0424)
Carhart Alphas	0.0024	0.0014	0.0004	0.0008	0.0007	0.0099	0.0097	0.0074	0.0053	0.0048
	(0.5580)	(0.7152)	(0.8949)	(0.7668)	(0.8044)	(0.0041)	(0.0028)	(0.0077)	(0.0355)	(0.0648)
Sharpe Ratio	0.07	0.03	0.00	0.04	0.05	0.41	0.47	0.43	0.35	0.35
	(0.7426)	(0.8639)	(0.9907)	(0.8425)	(0.7891)	(0.0246)	(0.0092)	(0.0155)	(0.0420)	(0.0480)

Table XXIV. Double-Sort Returns on Inflation-Beta Based Strategies, UK 1980 – 2013. This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	-0.0032	0.0021	0.0020	0.0049	0.0073	0.0033
	(0.2475)	(0.3824)	(0.4670)	(0.0812)	(0.0026)	(0.2214)
CAPM Alphas	-0.0038	0.0020	0.0017	0.0054	0.0072	0.0027
	(0.3478)	(0.5237)	(0.4984)	(0.1690)	(0.0151)	(0.2810)
FF Alphas	-0.0046	0.0014	0.0019	0.0050	0.0070	0.0025
	(0.2497)	(0.6542)	(0.4378)	(0.2103)	(0.0163)	(0.3242)
Carhart Alphas	-0.0060	-0.0005	0.0015	0.0071	0.0066	0.0058
	(0.1643)	(0.8835)	(0.6487)	(0.0863)	(0.0531)	(0.0313)
Sharpe Ratio	-0.2040	0.1540	0.1282	0.3079	0.5331	0.2157
	(0.4043)	(0.4819)	(0.4584)	(0.1890)	(0.0021)	(0.1868)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0018	0.0024	-0.0036	0.0082	0.0041	0.0023
	(0.5886)	(0.5438)	(0.4605)	(0.0139)	(0.2969)	(0.6382)
CAPM Alphas	0.0016	0.0023	-0.0044	0.0081	0.0029	0.0023
	(0.6866)	(0.6243)	(0.3683)	(0.0303)	(0.5377)	(0.6464)
FF Alphas	0.0016	0.0031	-0.0033	0.0080	0.0032	0.0041
	(0.6829)	(0.5265)	(0.5031)	(0.0373)	(0.5099)	(0.3920)
Carhart Alphas	0.0030	0.0024	-0.0065	0.0090	0.0040	0.0068
	(0.4805)	(0.6465)	(0.2433)	(0.0285)	(0.4161)	(0.2223)
Sharpe Ratio	0.0953	0.1070	-0.1301	0.4353	0.1839	0.0829
	(0.6418)	(0.6224)	(0.4704)	(0.0279)	(0.3881)	(0.6502)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0049	0.0011	0.0048	0.0062	0.0040	0.0111
	(0.2035)	(0.7494)	(0.1973)	(0.1063)	(0.2354)	(0.0031)
CAPM Alphas	0.0043	0.0006	0.0054	0.0060	0.0039	0.0118
	(0.3495)	(0.8794)	(0.1997)	(0.1861)	(0.2782)	(0.0024)
FF Alphas	0.0057	0.0001	0.0050	0.0070	0.0039	0.0118
	(0.2013)	(0.9704)	(0.2533)	(0.1145)	(0.2526)	(0.0032)
Carhart Alphas	0.0075	0.0027	0.0030	0.0052	0.0070	0.0130
	(0.0723)	(0.5158)	(0.5561)	(0.2426)	(0.0547)	(0.0054)
Sharpe Ratio	0.2243	0.0563	0.2274	0.2851	0.2093	0.5238
	(0.2976)	(0.7612)	(0.2555)	(0.1758)	(0.2425)	(0.0026)

6.2.6 Equal-Weighted Across All Signals

Table XXV. Equal-Weighted Portfolio across Signals, UK $1980-2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **Equal weighted portfolio across all signal-based strategies** takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of the respective signal-based long-short strategies. The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0011	0.0005	0.0000	0.0005	0.0007	0.0070	0.0076	0.0067	0.0053	0.0051
	(0.7086)	(0.8441)	(0.9898)	(0.8386)	(0.7814)	(0.0178)	(0.0059)	(0.0120)	(0.0388)	(0.0399)
CAPM Alphas	0.0012	0.0008	0.0002	0.0006	0.0006	0.0064	0.0071	0.0061	0.0047	0.0046
	(0.7032)	(0.7875)	(0.9354)	(0.8191)	(0.8263)	(0.0414)	(0.0140)	(0.0193)	(0.0475)	(0.0600)
FF Alphas	0.0021	0.0015	0.0009	0.0010	0.0009	0.0069	0.0076	0.0067	0.0053	0.0052
	(0.5126)	(0.6212)	(0.7537)	(0.6888)	(0.7162)	(0.0225)	(0.0076)	(0.0099)	(0.0281)	(0.0333)
Carhart Alphas	0.0024	0.0014	0.0004	0.0008	0.0007	0.0101	0.0099	0.0076	0.0055	0.0050
	(0.5580)	(0.7152)	(0.8949)	(0.7668)	(0.8044)	(0.0030)	(0.0020)	(0.0056)	(0.0265)	(0.0508)
Sharpe Ratio	0.07	0.03	0.00	0.04	0.05	0.42	0.49	0.44	0.37	0.36
	(0.7426)	(0.8639)	(0.9907)	(0.8425)	(0.7891)	(0.0198)	(0.0070)	(0.0122)	(0.0329)	(0.0379)

Table XXVI. Double-Sort Returns on Equal-Weighted Portfolio across Signals, UK $1980-2013$. This Table reports the profitability of two inflation-beta based long-short strategies for subgroups of stocks. At the end of each month t I first sort the investable stocks into terciles according to firm characteristics. Within each of the resulting terciles I sort the stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **Equal weighted portfolio across all signal-based strategies** takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of the respective signal-based long-short strategies. The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	TERCILE 1	TERCILE 2	TERCILE 3	TERCILE 1	TERCILE 2	TERCILE 3
Panel 1: Sorts by Size - Holding = 1 Month						
TS Mean	-0.0032	0.0021	0.0020	0.0064	0.0073	0.0034
	(0.2475)	(0.3824)	(0.4670)	(0.0212)	(0.0024)	(0.2098)
CAPM Alphas	-0.0038	0.0020	0.0017	0.0068	0.0072	0.0028
	(0.3478)	(0.5237)	(0.4984)	(0.0836)	(0.0140)	(0.2663)
FF Alphas	-0.0046	0.0014	0.0019	0.0065	0.0071	0.0026
	(0.2497)	(0.6542)	(0.4378)	(0.1076)	(0.0157)	(0.3070)
Carhart Alphas	-0.0060	-0.0005	0.0015	0.0088	0.0067	0.0059
	(0.1643)	(0.8835)	(0.6487)	(0.0348)	(0.0505)	(0.0268)
Sharpe Ratio	-0.2040	0.1540	0.1282	0.4076	0.5378	0.2212
	(0.4043)	(0.4819)	(0.4584)	(0.0835)	(0.0018)	(0.1761)
Panel 2: Sorts by Book-to-Market - Holding = 1 Month						
TS Mean	0.0018	0.0024	-0.0036	0.0080	0.0048	0.0037
	(0.5886)	(0.5438)	(0.4605)	(0.0155)	(0.2161)	(0.4433)
CAPM Alphas	0.0016	0.0023	-0.0044	0.0079	0.0036	0.0038
	(0.6866)	(0.6243)	(0.3683)	(0.0330)	(0.4365)	(0.4564)
FF Alphas	0.0016	0.0031	-0.0033	0.0079	0.0039	0.0055
	(0.6829)	(0.5265)	(0.5031)	(0.0401)	(0.4141)	(0.2493)
Carhart Alphas	0.0030	0.0024	-0.0065	0.0088	0.0051	0.0085
	(0.4805)	(0.6465)	(0.2433)	(0.0305)	(0.3058)	(0.1231)
Sharpe Ratio	0.0953	0.1070	-0.1301	0.4281	0.2182	0.1351
	(0.6418)	(0.6224)	(0.4704)	(0.0307)	(0.3052)	(0.4549)
Panel 3: Sorts by Beta IP - Holding = 1 Month						
TS Mean	0.0049	0.0011	0.0048	0.0073	0.0044	0.0112
	(0.2035)	(0.7494)	(0.1973)	(0.0586)	(0.1847)	(0.0027)
CAPM Alphas	0.0043	0.0006	0.0054	0.0071	0.0044	0.0119
	(0.3495)	(0.8794)	(0.1997)	(0.1221)	(0.2229)	(0.0021)
FF Alphas	0.0057	0.0001	0.0050	0.0080	0.0044	0.0119
	(0.2013)	(0.9704)	(0.2533)	(0.0707)	(0.2006)	(0.0029)
Carhart Alphas	0.0075	0.0027	0.0030	0.0063	0.0073	0.0131
	(0.0723)	(0.5158)	(0.5561)	(0.1539)	(0.0460)	(0.0048)
Sharpe Ratio	0.2243	0.0563	0.2274	0.3341	0.2340	0.5311
	(0.2976)	(0.7612)	(0.2555)	(0.1147)	(0.1889)	(0.0023)

6.2.7 Cumulative Log-Returns

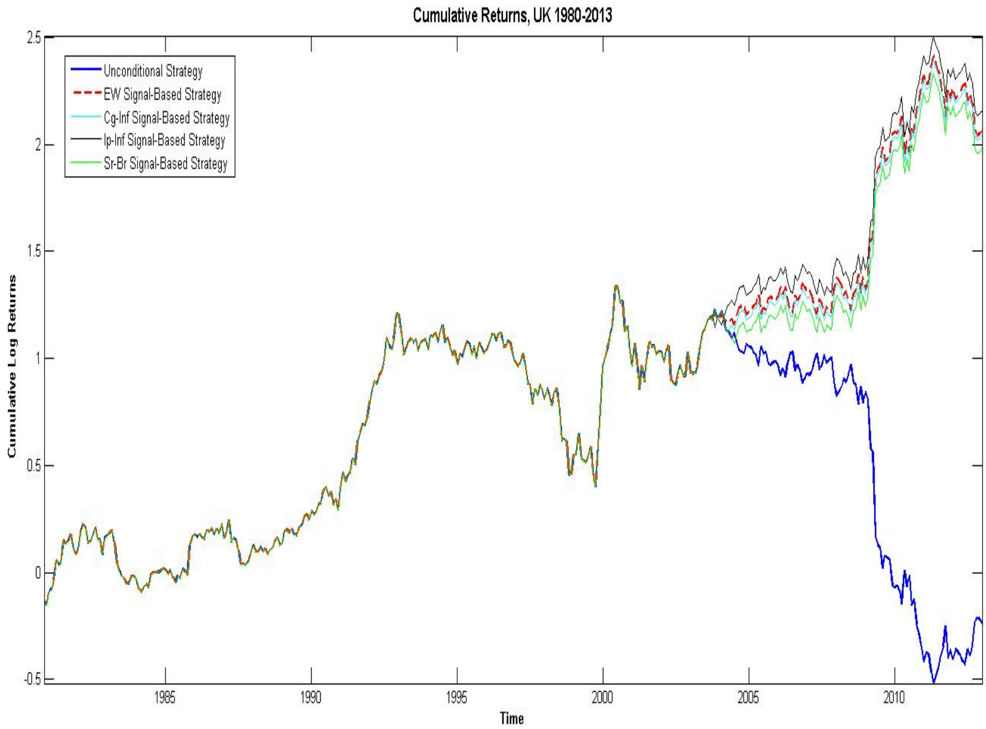


Figure 2. Cumulative Log-Returns on the Equal-Weighted Portfolio across the three Signal-Based Long-Short Strategies and on the three Signal-Based Long-Short Strategies versus the Cumulative Log-Returns on the Unconditional Inflation Beta Strategy.

APPENDIX

A Appendix

A.1 USA - 1965-2013: Robustness

A.1.1 Signal: Real GDP Growth - Inflation Correlations

Table I. Returns on Signal-Based Strategy for Alternative Signal Specifications, USA $1965-2013$**.** This Table reports the profitability of the signal-based long-short strategy when the strategy is implemented using k quarters of data to calculate the rolling correlations between yearly real GDP growth and yearly inflation, with k ranging from 12 to 61 quarters. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors and 2-sided p-values from Newey-West standard errors using 6 lags are reported. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

	CAPM		FF		CAR			CAPM		FF		CAR	
Lag	α	P-Value	α	P-Value	α	P-Value	**Lag**	α	P-Value	α	P-Value	α	P-Value
12	0.0006	0.836	0.0010	0.735	0.0025	0.3676	**37**	0.0080	0.0089***	0.0068	0.0154**	0.0069	0.0115**
13	0.0040	0.1648	0.0042	0.1353	0.0057	0.0375**	**38**	0.0080	0.0093***	0.0068	0.0162**	0.0069	0.0123**
14	0.0057	0.0556*	0.0052	0.0653*	0.0067	0.0152**	**39**	0.0081	0.0086***	0.0069	0.0148**	0.0070	0.0107**
15	0.0031	0.2714	0.0026	0.3209	0.0036	0.1608	**40**	0.0090	0.0042***	0.0077	0.0081***	0.0079	0.0047***
16	0.0018	0.5323	0.0012	0.6691	0.0027	0.3039	**41**	0.0080	0.0085***	0.0066	0.018**	0.0071	0.0087***
17	0.0047	0.0702*	0.0033	0.2008	0.0039	0.1294	**42**	0.0080	0.0085***	0.0066	0.018**	0.0071	0.0087***
18	0.0067	0.0219**	0.0051	0.0592*	0.0058	0.0295**	**43**	0.0080	0.0085***	0.0066	0.018**	0.0071	0.0087***
19	0.0070	0.0181**	0.0053	0.0587*	0.0061	0.0265**	**44**	0.0076	0.01**	0.0060	0.0259**	0.0057	0.0269**
20	0.0065	0.0292**	0.0049	0.0807*	0.0054	0.0468**	**45**	0.0068	0.0239**	0.0053	0.0477**	0.0038	0.1478
21	0.0064	0.0318**	0.0048	0.081*	0.0052	0.0536*	**46**	0.0063	0.037**	0.0049	0.0712*	0.0031	0.2462
22	0.0062	0.0275**	0.0046	0.0727*	0.0051	0.0383**	**47**	0.0063	0.0368**	0.0049	0.0705*	0.0031	0.2441
23	0.0076	0.0098***	0.0062	0.0213**	0.0063	0.0135**	**48**	0.0062	0.0381**	0.0049	0.0729*	0.0030	0.2543
24	0.0070	0.0152**	0.0057	0.0277**	0.0058	0.0212**	**49**	0.0062	0.0399**	0.0049	0.0743*	0.0031	0.2517
25	0.0066	0.0222**	0.0053	0.044**	0.0054	0.0344**	**50**	0.0060	0.0473**	0.0047	0.0874*	0.0029	0.2831
26	0.0064	0.0287**	0.0050	0.0559*	0.0051	0.0438**	**51**	0.0062	0.0394**	0.0049	0.0745*	0.0031	0.2452
27	0.0057	0.0542*	0.0044	0.1047	0.0045	0.0967*	**52**	0.0062	0.0405**	0.0048	0.0781*	0.0030	0.2564
28	0.0064	0.0398**	0.0052	0.073*	0.0052	0.0731*	**53**	0.0066	0.0284**	0.0052	0.0569*	0.0034	0.2083
29	0.0057	0.0699*	0.0045	0.1257	0.0045	0.1162	**54**	0.0067	0.0257**	0.0053	0.0541*	0.0034	0.2036
30	0.0056	0.0746*	0.0044	0.1327	0.0044	0.1286	**55**	0.0063	0.0367**	0.0048	0.0765*	0.0030	0.2603
31	0.0061	0.0541*	0.0049	0.0948*	0.0049	0.089*	**56**	0.0062	0.0377**	0.0048	0.0795*	0.0030	0.2688
32	0.0060	0.0598*	0.0047	0.1144	0.0048	0.1014	**57**	0.0060	0.0463**	0.0046	0.0908*	0.0029	0.285
33	0.0076	0.0137**	0.0064	0.0251**	0.0068	0.0142**	**58**	0.0069	0.0214**	0.0052	0.0549*	0.0047	0.0792*
34	0.0081	0.0079***	0.0069	0.0133**	0.0072	0.0076***	**59**	0.0063	0.0364**	0.0049	0.0743*	0.0031	0.2511
35	0.0087	0.0045***	0.0077	0.0064***	0.0080	0.0047***	**60**	0.0062	0.0403**	0.0047	0.0841*	0.0029	0.2831
36	0.0084	0.006***	0.0071	0.0106**	0.0073	0.0075***	**61**	0.0061	0.0438**	0.0046	0.0905*	0.0028	0.2974

A.1.2 Signal: Industrial Production Growth - Inflation Correlations

Table II. Returns on Signal-Based Strategy for Alternative Signal Specifications, USA 1965 − 2013**.** This Table reports the profitability of the signal-based long-short strategy when the strategy is implemented using k months of data to calculate the rolling correlations between yearly industrial production growth and yearly inflation, with k ranging from 34 to 180 months. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors and 2-sided p-values from Newey-West standard errors using 6 lags are reported. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

	CAPM		**FF**		**CAR**			**CAPM**		**FF**		**CAR**	
Lag	α	P-Value	α	P-Value	α	P-Value	**Lag**	α	P-Value	α	P-Value	α	P-Value
34	0.0029	0.3594	0.0008	0.7727	0.0033	0.2342	**108**	0.0078	0.0055***	0.0069	0.0086***	0.0076	0.0034***
36	0.0023	0.4629	0.0010	0.7439	0.0029	0.312	**110**	0.0091	0.0017***	0.0081	0.0025***	0.0084	0.0014***
38	0.0019	0.5546	0.0002	0.9587	0.0026	0.366	**112**	0.0083	0.0037***	0.0072	0.0069***	0.0076	0.0038***
40	0.0031	0.2915	0.0016	0.581	0.0037	0.1716	**114**	0.0073	0.0091***	0.0062	0.0163**	0.0066	0.0096***
42	0.0049	0.0947*	0.0032	0.2473	0.0053	0.0483**	**116**	0.0063	0.0251**	0.0052	0.0474**	0.0055	0.0349**
44	0.0059	0.0378**	0.0043	0.1167	0.0062	0.0179**	**118**	0.0063	0.0342**	0.0050	0.0683*	0.0053	0.0567*
46	0.0062	0.0319**	0.0047	0.0903*	0.0065	0.0156**	**120**	0.0066	0.0256**	0.0053	0.0503*	0.0055	0.0424**
48	0.0072	0.0107**	0.0056	0.0392**	0.0069	0.0108**	**122**	0.0075	0.0119**	0.0061	0.0262**	0.0066	0.0159**
50	0.0075	0.0084***	0.0062	0.0262**	0.0071	0.0111**	**124**	0.0067	0.0243**	0.0053	0.0532*	0.0061	0.0234**
52	0.0082	0.0061***	0.0069	0.0149**	0.0078	0.0061***	**126**	0.0060	0.0463**	0.0045	0.1056	0.0056	0.0381**
54	0.0077	0.0096***	0.0063	0.0257**	0.0070	0.0135**	**128**	0.0061	0.0439**	0.0047	0.0986*	0.0058	0.0366**
56	0.0077	0.0085***	0.0063	0.0226**	0.0062	0.0219**	**130**	0.0058	0.0529*	0.0042	0.1263	0.0052	0.0502*
58	0.0071	0.0166**	0.0056	0.0443**	0.0051	0.0672*	**132**	0.0066	0.0317**	0.0050	0.0779*	0.0059	0.0293**
60	0.0075	0.0141**	0.0060	0.0346**	0.0053	0.0621*	**134**	0.0063	0.0369**	0.0044	0.1004	0.0052	0.0387**
62	0.0073	0.0158**	0.0058	0.0398**	0.0050	0.0784*	**136**	0.0061	0.0432**	0.0042	0.1244	0.0043	0.0943*
64	0.0071	0.0202**	0.0056	0.0508*	0.0043	0.137	**138**	0.0058	0.0545*	0.0038	0.1551	0.0040	0.1229
66	0.0065	0.0377**	0.0050	0.0871*	0.0038	0.2051	**140**	0.0059	0.0462**	0.0040	0.1293	0.0040	0.1253
68	0.0069	0.0248**	0.0055	0.0597*	0.0043	0.1436	**142**	0.0059	0.0475**	0.0041	0.1281	0.0038	0.1502
70	0.0068	0.0284**	0.0053	0.0663*	0.0042	0.1603	**144**	0.0061	0.0395**	0.0043	0.1073	0.0040	0.1252
72	0.0069	0.0276**	0.0055	0.0575*	0.0045	0.1258	**146**	0.0066	0.0266**	0.0049	0.069*	0.0046	0.0837*
74	0.0061	0.0463**	0.0049	0.085*	0.0038	0.1966	**148**	0.0068	0.023**	0.0051	0.0599*	0.0048	0.0747*
76	0.0062	0.0426**	0.0051	0.0754*	0.0039	0.1764	**150**	0.0065	0.0292**	0.0049	0.0718*	0.0046	0.088*
78	0.0062	0.0418**	0.0051	0.0746*	0.0039	0.1768	**152**	0.0063	0.036**	0.0047	0.0841*	0.0042	0.1148
80	0.0057	0.0612*	0.0046	0.103	0.0034	0.2313	**154**	0.0068	0.0219**	0.0053	0.0515*	0.0047	0.0798*
82	0.0052	0.0897*	0.0040	0.1583	0.0029	0.3244	**156**	0.0066	0.0259**	0.0051	0.0599*	0.0045	0.0908*
84	0.0056	0.0664*	0.0045	0.1195	0.0034	0.2535	**158**	0.0069	0.0204**	0.0053	0.049**	0.0048	0.0733*
86	0.0057	0.0648*	0.0046	0.113	0.0034	0.2497	**160**	0.0067	0.0258**	0.0051	0.0617*	0.0045	0.0916*
88	0.0063	0.0402**	0.0054	0.0659*	0.0049	0.0977*	**162**	0.0068	0.0221**	0.0052	0.0537*	0.0047	0.08*
90	0.0052	0.0848*	0.0041	0.1448	0.0039	0.1716	**164**	0.0073	0.0136**	0.0057	0.0346**	0.0051	0.0558*
92	0.0033	0.2816	0.0023	0.4088	0.0022	0.4346	**166**	0.0073	0.0139**	0.0057	0.0355**	0.0051	0.0574*
94	0.0049	0.0848*	0.0039	0.1494	0.0041	0.1291	**168**	0.0073	0.0137**	0.0057	0.037**	0.0050	0.0608*
96	0.0050	0.0784*	0.0040	0.1375	0.0044	0.1098	**170**	0.0070	0.0179**	0.0053	0.0479**	0.0047	0.0772*
98	0.0047	0.1107	0.0035	0.1984	0.0039	0.1612	**172**	0.0068	0.0215**	0.0052	0.0572*	0.0045	0.0891*
100	0.0067	0.0167**	0.0060	0.0206**	0.0064	0.0124**	**174**	0.0066	0.0269**	0.0050	0.0672*	0.0044	0.1003
102	0.0066	0.0203**	0.0058	0.0284**	0.0066	0.0102**	**176**	0.0067	0.0237**	0.0051	0.0587*	0.0046	0.0869*
104	0.0068	0.0182**	0.0060	0.0242**	0.0068	0.009***	**178**	0.0067	0.0236**	0.0051	0.0585*	0.0046	0.0846*
106	0.0080	0.0042***	0.0071	0.0066***	0.0078	0.0024***	**180**	0.0067	0.0238**	0.0051	0.0593*	0.0046	0.0858*

A.1.3 Signal: Stock - Bond Correlations

Table III. Returns on Signal-Based Strategy for Alternative Signal Specifications, USA 1965 – 2013**.** This Table reports the profitability of the signal-based long-short strategy when the strategy is implemented using k months of data to calculate the (smoothed) rolling correlations between monthly series of yearly stock and bond returns, with k ranging from 34 to 180 months. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors and 2-sided p-values from Newey-West standard errors using 6 lags are reported. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

	CAPM		**FF**		**CAR**			**CAPM**		**FF**		**CAR**	
Lag	α	P-Value	α	P-Value	α	P-Value	**Lag**	α	P-Value	α	P-Value	α	P-Value
34	0.0031	0.3147	0.0021	0.4637	0.0043	0.1229	**108**	0.0087	0.0033***	0.0086	0.0018***	0.0063	0.0357**
36	0.0042	0.1663	0.0033	0.2518	0.0055	0.0525*	**110**	0.0089	0.0027***	0.0089	0.0013***	0.0065	0.0291**
38	0.0044	0.1294	0.0032	0.2484	0.0046	0.0883*	**112**	0.0086	0.0037***	0.0086	0.0019***	0.0063	0.0374**
40	0.0049	0.0878*	0.0036	0.1832	0.0046	0.0871*	**114**	0.0087	0.0033***	0.0087	0.0016***	0.0064	0.0345**
42	0.0054	0.0544*	0.0039	0.1444	0.0047	0.083*	**116**	0.0085	0.0045***	0.0085	0.0022***	0.0062	0.0401**
44	0.0057	0.0462**	0.0041	0.13	0.0048	0.0781*	**118**	0.0086	0.0037***	0.0087	0.0017***	0.0064	0.0336**
46	0.0064	0.0269**	0.0049	0.0811*	0.0054	0.056*	**120**	0.0085	0.0044***	0.0085	0.0021***	0.0063	0.0376**
48	0.0069	0.0212**	0.0051	0.0779*	0.0051	0.079*	**122**	0.0086	0.004***	0.0086	0.0018***	0.0064	0.0343**
50	0.0073	0.0143**	0.0054	0.0595*	0.0055	0.055*	**124**	0.0086	0.0039***	0.0086	0.0018***	0.0064	0.0342**
52	0.0077	0.0089***	0.0057	0.0408**	0.0058	0.0444**	**126**	0.0088	0.0031***	0.0088	0.0013***	0.0066	0.0278**
54	0.0092	0.0025***	0.0072	0.0125**	0.0068	0.0237**	**128**	0.0087	0.0033***	0.0088	0.0014***	0.0065	0.0289**
56	0.0088	0.0031***	0.0071	0.0129**	0.0065	0.0299**	**130**	0.0089	0.0026***	0.0090	0.0011***	0.0067	0.0249**
58	0.0087	0.0038***	0.0069	0.0162**	0.0061	0.0428**	**132**	0.0086	0.0036***	0.0087	0.0016***	0.0064	0.0315**
60	0.0102	0.0006***	0.0084	0.0031***	0.0077	0.0101**	**134**	0.0083	0.0049***	0.0084	0.0022***	0.0061	0.0398**
62	0.0099	0.0008***	0.0082	0.0038***	0.0074	0.0144**	**136**	0.0082	0.0055***	0.0082	0.0025***	0.0060	0.0441**
64	0.0104	0.0003***	0.0086	0.0021***	0.0078	0.0095***	**138**	0.0078	0.0082***	0.0078	0.0043***	0.0055	0.0638*
66	0.0112	0.0001***	0.0093	0.001***	0.0084	0.0058***	**140**	0.0072	0.0151**	0.0071	0.01**	0.0049	0.1067
68	0.0109	0.0002***	0.0091	0.0013***	0.0081	0.008***	**142**	0.0066	0.0281**	0.0064	0.0211**	0.0043	0.1561
70	0.0107	0.0003***	0.0087	0.0019***	0.0075	0.0114**	**144**	0.0065	0.0309**	0.0062	0.0249**	0.0044	0.1428
72	0.0099	0.0006***	0.0084	0.0022***	0.0069	0.0199**	**146**	0.0064	0.034**	0.0061	0.0278**	0.0043	0.1544
74	0.0092	0.0017***	0.0080	0.0036***	0.0061	0.0412**	**148**	0.0058	0.0547*	0.0056	0.0448**	0.0039	0.2029
76	0.0103	0.0004***	0.0091	0.0008***	0.0070	0.0177**	**150**	0.0055	0.0735*	0.0052	0.0712*	0.0037	0.2147
78	0.0103	0.0003***	0.0091	0.0007***	0.0071	0.0156**	**152**	0.0059	0.0558*	0.0054	0.0567*	0.0041	0.1798
80	0.0103	0.0003***	0.0095	0.0003***	0.0077	0.0081***	**154**	0.0057	0.0628*	0.0053	0.0632*	0.0039	0.1936
82	0.0101	0.0005***	0.0094	0.0004***	0.0071	0.0154**	**156**	0.0052	0.0868*	0.0048	0.0918*	0.0034	0.2521
84	0.0108	0.0002***	0.0102	0.0001***	0.0079	0.0071***	**158**	0.0047	0.1197	0.0040	0.1491	0.0025	0.3656
86	0.0103	0.0003***	0.0097	0.0003***	0.0074	0.0117**	**160**	0.0037	0.2327	0.0032	0.2706	0.0006	0.8417
88	0.0105	0.0002***	0.0099	0.0002***	0.0075	0.0118**	**162**	0.0035	0.2583	0.0031	0.2852	0.0003	0.9034
90	0.0104	0.0003***	0.0098	0.0003***	0.0074	0.014**	**164**	0.0040	0.191	0.0038	0.1908	0.0013	0.629
92	0.0110	0.0001***	0.0105	0.0001***	0.0081	0.0066***	**166**	0.0042	0.174	0.0039	0.1727	0.0015	0.5968
94	0.0102	0.0004***	0.0097	0.0003***	0.0074	0.0125**	**168**	0.0042	0.1734	0.0039	0.1709	0.0015	0.5764
96	0.0105	0.0002***	0.0102	0.0001***	0.0078	0.0077***	**170**	0.0041	0.1841	0.0038	0.1855	0.0014	0.6072
98	0.0102	0.0003***	0.0102	0.0001***	0.0078	0.0075***	**172**	0.0037	0.2238	0.0035	0.2286	0.0011	0.6948
100	0.0095	0.001***	0.0094	0.0005***	0.0071	0.0158**	**174**	0.0034	0.2663	0.0032	0.2713	0.0008	0.7755
102	0.0089	0.0025***	0.0089	0.0012***	0.0064	0.0329**	**176**	0.0038	0.2166	0.0036	0.2108	0.0012	0.6646
104	0.0087	0.0034***	0.0085	0.002***	0.0061	0.0426**	**178**	0.0036	0.2348	0.0035	0.2312	0.0011	0.6928
106	0.0087	0.0033***	0.0086	0.0019***	0.0062	0.04**	**180**	0.0041	0.1838	0.0038	0.1833	0.0013	0.6389

A.2 USA - 1940-2013

A.2.1 Summary Statistics

Table IV. Summary Statistics for Inflation-Beta Portfolios, USA $1940 - 2013$**.** This Table reports summary statistics on 10 inflation-beta portfolios. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The portfolios are rebalanced monthly. **Column two** reports the average inflation-betas for the stocks in each of the ten portfolios. **Column three** (**Column four**) reports the average returns (standard deviations) on the ten portfolios. **Column five** and **Column six** contain the average number of stocks in each of the ten portfolios and the average portfolio turnover, respectively.

Inflation Portfolios 1940-2013 - Summary Statistics					
Portfolios	**Average Inflation Betas**	**Average Return**	**STD**	**Average # Stocks**	**Average Turnover**
1	-8.03	1.15	6.20	211.75	0.17
2	-4.58	1.13	5.35	211.82	0.33
3	-3.33	1.08	4.92	211.74	0.41
4	-2.46	1.05	4.63	211.82	0.46
5	-1.75	0.95	4.45	211.55	0.48
6	-1.15	0.90	4.47	212.04	0.47
7	-0.53	0.99	4.70	211.72	0.45
8	0.20	0.97	4.77	211.83	0.40
9	1.34	1.01	5.24	211.73	0.31
10	4.95	0.88	6.73	211.84	0.17
Spread 1 - 10	*-12.98*	*0.26*	*-0.53*		

A.2.2 Signal: Industrial Production Growth - Inflation Correlations

Table V. Returns on Inflation-Beta Based Strategies I, USA $1940 - 2013$**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**π-Beta Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0028	0.0032	0.0028	0.0055	0.0041	0.0042
	(0.2069)	(0.1138)	(0.1812)	(0.0066)	(0.0273)	(0.0307)
Market-rf	-0.0271	-0.0668	-0.0623	0.2022	0.1911	0.1902
	(0.7560)	(0.3665)	(0.3619)	(0.0123)	(0.0026)	(0.0012)
SMB		0.1555	0.1568		0.1806	0.1803
		(0.2837)	(0.2960)		(0.1313)	(0.1312)
HML		-0.1021	-0.0927		0.2482	0.2463
		(0.5652)	(0.6107)		(0.1139)	(0.1311)
MOM			0.0460			-0.0095
			(0.7520)			(0.9424)
OBS	875	875	875	875	875	875
adj.R^2	-0.0007	0.0065	0.0065	0.0262	0.0469	0.0458
Panel 2: Alphas for Long-Leg						
Alpha	0.0004	0.0008	0.0004	0.0017	0.0013	0.0011
	(0.7694)	(0.4035)	(0.7003)	(0.1614)	(0.2272)	(0.3702)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0024	-0.0023	-0.0024	-0.0038	-0.0028	-0.0031
	(0.1052)	(0.0989)	(0.0977)	(0.0049)	(0.0239)	(0.0060)

Table VI. Returns on Inflation-Beta Based Strategies II, USA 1940 − 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**π-Beta Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0026	0.0023	0.0021	0.0022	0.0022	0.0068	0.0068	0.0064	0.0061	0.0058
	(0.1486)	(0.1990)	(0.2307)	(0.1962)	(0.1826)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
CAPM Alphas	0.0028	0.0024	0.0021	0.0021	0.0020	0.0055	0.0054	0.0050	0.0047	0.0042
	(0.2069)	(0.2582)	(0.3108)	(0.2870)	(0.2876)	(0.0066)	(0.0057)	(0.0081)	(0.0099)	(0.0151)
FF Alphas	0.0032	0.0029	0.0028	0.0029	0.0030	0.0041	0.0042	0.0040	0.0039	0.0036
	(0.1138)	(0.1282)	(0.1420)	(0.1118)	(0.0941)	(0.0273)	(0.0194)	(0.0232)	(0.0221)	(0.0288)
Carhart Alphas	0.0028	0.0024	0.0021	0.0022	0.0024	0.0042	0.0041	0.0034	0.0030	0.0025
	(0.1812)	(0.2408)	(0.2856)	(0.2248)	(0.1893)	(0.0307)	(0.0351)	(0.0668)	(0.0951)	(0.1399)
Sharpe Ratio	0.17	0.15	0.14	0.15	0.16	0.44	0.45	0.44	0.43	0.42
	(0.1942)	(0.2481)	(0.2778)	(0.2388)	(0.2241)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0004)

A.2.3 Signal: Industrial Production Growth - Inflation Correlations $1940-1965$, Equal-Weighted Across all Signals $1965-2013$

Table VII. Industrial Production Growth - Inflation Correlations $1940-1965$, Equal-Weighted Portfolio across Signals $1965-2013$ I. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **Equal weighted portfolio across all signal-based strategies** takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of the respective signal-based long-short strategies for the period $1965-2013$. For the period $1940-1965$ it is the industrial production-inflation signal-based strategy. The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**π-Beta Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0028	0.0032	0.0028	0.0062	0.0044	0.0037
	(0.2069)	(0.1138)	(0.1812)	(0.0011)	(0.0108)	(0.0439)
Market-rf	-0.0271	-0.0668	-0.0623	0.1336	0.1321	0.1399
	(0.7560)	(0.3665)	(0.3619)	(0.0744)	(0.0224)	(0.0098)
SMB		0.1555	0.1568		0.1683	0.1706
		(0.2837)	(0.2960)		(0.0824)	(0.1011)
HML		-0.1021	-0.0927		0.3233	0.3398
		(0.5652)	(0.6107)		(0.0223)	(0.0177)
MOM			0.0460			0.0804
			(0.7520)			(0.4991)
OBS	875	875	875	875	875	875
adj.R^2	-0.0007	0.0065	0.0065	0.0148	0.0562	0.0595
Panel 2: Alphas for Long-Leg						
Alpha	0.0004	0.0008	0.0004	0.0020	0.0014	0.0009
	(0.7694)	(0.4035)	(0.7003)	(0.0770)	(0.1581)	(0.4695)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0024	-0.0023	-0.0024	-0.0041	-0.0030	-0.0029
	(0.1052)	(0.0989)	(0.0977)	(0.0016)	(0.0128)	(0.0088)

Table VIII. Industrial Production Growth - Inflation Correlations $1940-1965$**, Equal-Weighted Portfolio across Signals** $1965-2013$ **II.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **Equal weighted portfolio across all signal-based strategies** takes equal-weighted positions in all three signal-based zero-investment portfolios by investing one third of the wealth into each of the respective signal-based long-short strategies for the period $1965-2013$. For the period $1940-1965$ it is the industrial production-inflation signal-based strategy. The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**π-Beta Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0026	0.0023	0.0021	0.0022	0.0022	0.0070	0.0070	0.0067	0.0064	0.0061
	(0.1486)	(0.1990)	(0.2307)	(0.1962)	(0.1826)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CAPM Alphas	0.0028	0.0024	0.0021	0.0021	0.0020	0.0062	0.0061	0.0058	0.0054	0.0050
	(0.2069)	(0.2582)	(0.3108)	(0.2870)	(0.2876)	(0.0011)	(0.0008)	(0.0010)	(0.0012)	(0.0016)
FF Alphas	0.0032	0.0029	0.0028	0.0029	0.0030	0.0044	0.0045	0.0044	0.0043	0.0041
	(0.1138)	(0.1282)	(0.1420)	(0.1118)	(0.0941)	(0.0108)	(0.0067)	(0.0070)	(0.0063)	(0.0074)
Carhart Alphas	0.0028	0.0024	0.0021	0.0022	0.0024	0.0037	0.0037	0.0031	0.0027	0.0024
	(0.1812)	(0.2408)	(0.2856)	(0.2248)	(0.1893)	(0.0439)	(0.0453)	(0.0717)	(0.0948)	(0.1246)
Sharpe Ratio	0.17	0.15	0.14	0.15	0.16	0.53	0.54	0.53	0.53	0.51
	(0.1942)	(0.2481)	(0.2778)	(0.2388)	(0.2241)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

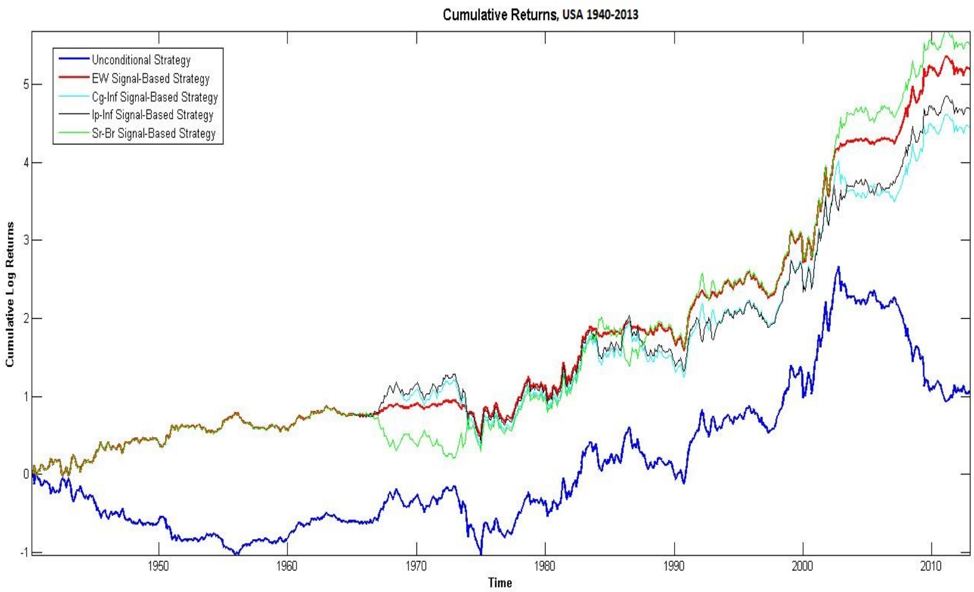


Figure 1. Cumulative Log-Returns on the Equal-Weighted Portfolio across the three Signal-Based Long-Short Strategies and on the three Signal-Based Long-Short Strategies versus the Cumulative Log-Returns on the Unconditional Inflation Beta Strategy. All the Signal-Based Long-Short Strategies are based on the Industrial Production Growth-Inflation Signal from $1940-1965$.

Table IX. Fama and MacBeth (1973) Regression Results, U.S. $1940-2013$. This Table reports the results of a cross-sectional Fama and MacBeth (1973) regression over the entire sample period, and for the pro- and countercyclical inflation states separately. Employing the inflation-betas estimated in equation (1), I run a cross-sectional regression every month t of the excess returns ($R^e_{n,t} = R_{n,t} - R^f_t$) on the n stocks that are in the universe of investable stocks in month t onto a constant and their time t inflation-betas ($\hat{\beta}_{n,t}$) from equation (1) : $R^e_{n,t} = \gamma_t + \lambda_t \hat{\beta}_{n,t} + \varepsilon_t,\ n = 1, ..., N$. To get an estimate of the market price of inflation risk for pro-/countercyclical inflation states separately, I run the Fama and MacBeth (1973) regression by only considering the months t for which the signal indicates pro-/countercyclical inflation states. The resulting estimates $\hat{\gamma}_t$ and $\hat{\lambda}_t$ are averaged over time ($\overline{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t$ and $\overline{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t$). Two-sided p-Values are reported in parentheses.

Fama-MacBeth Cross Sectional Regressions: U.S. 1940-2013						
Signal	**Entire Sample**		**Countercyclical**		**Procyclical**	
	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$
Δ Ind. Prod. - Inflation	0.0082	0.00004	0.0064	-0.0003	0.0106	0.0005
	(0.0000)	(0.8226)	(0.0035)	(0.0239)	(0.0000)	(0.2360)
Comb. w. Δ Real GDP - Inf	0.0082	0.00004	0.0071	-0.0002	0.0101	0.0005
	(0.0000)	(0.8226)	(0.0006)	(0.0332)	(0.0001)	(0.2473)
Comb. w. Stock - Bond	0.0082	0.00004	0.0085	-0.0004	0.0080	0.0003
	(0.0000)	(0.8226)	(0.0007)	(0.0055)	(0.0002)	(0.2316)

A.3 USA - 1952-2013

A.3.1 Summary Statistics

Table X. Summary Statistics for Inflation-Beta Portfolios, USA $1952 - 2013$**.** This Table reports summary statistics on 10 inflation-beta portfolios. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The portfolios are rebalanced monthly. **Column two** reports the average inflation betays for the stocks in each of the ten portfolios. **Column three** (**Column four**) reports the average returns (standard deviations) on the ten portfolios. **Column five** and **Column six** contain the average number of stocks in each of the ten portfolios and the average portfolio turnover, respectively.

Inflation Portfolios 1952-2013 - Summary Statistics					
Portfolios	**Average Inflation-β**	**Average Return**	**STD**	**Average # Stocks**	**Average Turnover**
1	-9.42	1.19	6.43	240.10	0.18
2	-5.43	1.18	5.56	240.17	0.33
3	-3.99	1.09	5.05	240.09	0.42
4	-3.00	1.06	4.67	240.16	0.46
5	-2.21	0.92	4.44	239.90	0.48
6	-1.53	0.86	4.45	240.39	0.47
7	-0.85	0.92	4.72	240.07	0.45
8	-0.03	0.89	4.75	240.18	0.41
9	1.23	0.89	5.12	240.07	0.32
10	5.33	0.78	6.81	240.19	0.18
Spread 1 - 10	*-14.74*	*0.41*	*-0.37*		

A.3.2 Signal: Industrial Production Growth - Inflation Correlations

Table XI. Returns on Inflation-Beta Based Strategies I, USA 1952 − 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0040	0.0032	0.0019	0.0061	0.0052	0.0059
	(0.1149)	(0.1599)	(0.4214)	(0.0092)	(0.0143)	(0.0066)
Market-rf	0.0228	-0.0020	0.0204	0.1899	0.1887	0.1771
	(0.8193)	(0.9804)	(0.7699)	(0.0422)	(0.0069)	(0.0043)
SMB		0.2504	0.2567		0.1479	0.1446
		(0.0809)	(0.1023)		(0.2601)	(0.2533)
HML		0.1230	0.1690		0.1521	0.1283
		(0.5191)	(0.3813)		(0.4272)	(0.5384)
MOM			0.1404			-0.0728
			(0.3595)			(0.6213)
OBS	731	731	731	731	731	731
adj.R^2	-0.0011	0.0134	0.0218	0.0210	0.0276	0.0289
Panel 2: Alphas for Long-Leg						
Alpha	0.0010	0.0010	0.0002	0.0021	0.0020	0.0022
	(0.4516)	(0.3659)	(0.8554)	(0.1397)	(0.0849)	(0.0934)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0030	-0.0022	-0.0017	-0.0040	-0.0032	-0.0037
	(0.0891)	(0.1731)	(0.3007)	(0.0110)	(0.0286)	(0.0053)

Table XII. Returns on Inflation-Beta Based Strategies II, USA 1952 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0041	0.0038	0.0036	0.0038	0.0038	0.0071	0.0070	0.0065	0.0062	0.0058
	(0.0453)	(0.0593)	(0.0629)	(0.0477)	(0.0426)	(0.0005)	(0.0005)	(0.0008)	(0.0011)	(0.0017)
CAPM Alphas	0.0040	0.0036	0.0034	0.0034	0.0033	0.0061	0.0059	0.0053	0.0049	0.0045
	(0.1149)	(0.1386)	(0.1551)	(0.1352)	(0.1346)	(0.0092)	(0.0088)	(0.0141)	(0.0173)	(0.0250)
FF Alphas	0.0032	0.0030	0.0029	0.0031	0.0031	0.0052	0.0053	0.0049	0.0048	0.0046
	(0.1599)	(0.1710)	(0.1786)	(0.1463)	(0.1320)	(0.0143)	(0.0103)	(0.0138)	(0.0125)	(0.0150)
Carhart Alphas	0.0019	0.0015	0.0012	0.0014	0.0015	0.0059	0.0057	0.0048	0.0043	0.0039
	(0.4214)	(0.5083)	(0.5691)	(0.4882)	(0.4496)	(0.0066)	(0.0085)	(0.0216)	(0.0315)	(0.0450)
Sharpe Ratio	0.26	0.24	0.24	0.25	0.26	0.45	0.45	0.43	0.42	0.40
	(0.0742)	(0.0917)	(0.0930)	(0.0714)	(0.0647)	(0.0005)	(0.0004)	(0.0008)	(0.0013)	(0.0022)

A.3.3 Signal: Stock - Bond Correlations

Table XIII. Returns on Inflation-Beta Based Strategies I, USA **1952 − 2013.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. **Panel 1** reports alpha estimates, factor loadings and adjusted R^2's resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors. **Panel 2** (**Panel 3**) contains the alpha estimates from regressing the monthly excess returns on the long-leg (short-leg) of the respective inflation-beta strategies on widely accepted risk factors. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy			**Signal-Based Strategy**		
	CAPM	Fama-French	Carhart	CAPM	Fama-French	Carhart
Panel 1: Factor Regressions - Holding = 1 Month						
Alpha	0.0040	0.0032	0.0019	0.0076	0.0058	0.0051
	(0.1149)	(0.1599)	(0.4214)	(0.0022)	(0.0133)	(0.0439)
Market-rf	0.0228	-0.0020	0.0204	0.0114	0.0785	0.0891
	(0.8193)	(0.9804)	(0.7699)	(0.9045)	(0.2757)	(0.1873)
SMB		0.2504	0.2567		0.0015	0.0045
		(0.0809)	(0.1023)		(0.9893)	(0.9685)
HML		0.1230	0.1690		0.4002	0.4219
		(0.5191)	(0.3813)		(0.0116)	(0.0129)
MOM			0.1404			0.0663
			(0.3595)			(0.6361)
OBS	731	731	731	731	731	731
adj.R^2	-0.0011	0.0134	0.0218	-0.0013	0.0323	0.0331
Panel 2: Alphas for Long-Leg						
Alpha	0.0010	0.0010	0.0002	0.0028	0.0023	0.0018
	(0.4516)	(0.3659)	(0.8554)	(0.0555)	(0.0977)	(0.2481)
Panel 3: Alphas for Short-Leg						
Alpha	-0.0030	-0.0022	-0.0017	-0.0047	-0.0035	-0.0033
	(0.0891)	(0.1731)	(0.3007)	(0.0031)	(0.0152)	(0.0158)

Table XIV. Returns on Inflation-Beta Based Strategies II, USA 1952 − 2013**.** This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0041	0.0038	0.0036	0.0038	0.0038	0.0077	0.0077	0.0074	0.0071	0.0068
	(0.0453)	(0.0593)	(0.0629)	(0.0477)	(0.0426)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
CAPM Alphas	0.0040	0.0036	0.0034	0.0034	0.0033	0.0076	0.0076	0.0073	0.0069	0.0065
	(0.1149)	(0.1386)	(0.1551)	(0.1352)	(0.1346)	(0.0022)	(0.0014)	(0.0016)	(0.0020)	(0.0025)
FF Alphas	0.0032	0.0030	0.0029	0.0031	0.0031	0.0058	0.0060	0.0059	0.0058	0.0056
	(0.1599)	(0.1710)	(0.1786)	(0.1463)	(0.1320)	(0.0133)	(0.0080)	(0.0078)	(0.0080)	(0.0084)
Carhart Alphas	0.0019	0.0015	0.0012	0.0014	0.0015	0.0051	0.0052	0.0048	0.0044	0.0042
	(0.4214)	(0.5083)	(0.5691)	(0.4882)	(0.4496)	(0.0439)	(0.0372)	(0.0460)	(0.0571)	(0.0611)
Sharpe Ratio	0.26	0.24	0.24	0.25	0.26	0.48	0.50	0.49	0.48	0.48
	(0.0742)	(0.0917)	(0.0930)	(0.0714)	(0.0647)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0003)

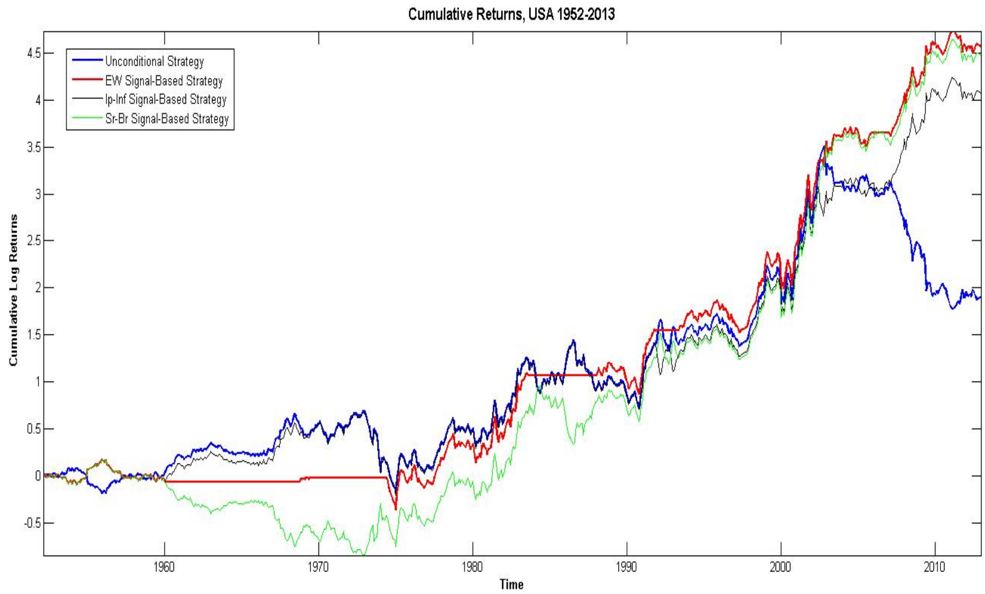


Figure 2. Cumulative Log-Returns on the Equal-Weighted Portfolio across the two Signal-Based Long-Short Strategies and on the two Signal-Based Long-Short Strategies versus the Cumulative Log-Returns on the Unconditional Inflation Beta Strategy.

Table XV. Fama and MacBeth (1973) Regression Results, USA $1952-2013$**.** This Table reports the results of a cross-sectional Fama and MacBeth (1973) regression over the entire sample period, and for the pro- and countercyclical inflation states separately. Employing the inflation-betas estimated in equation (1), I run a cross-sectional regression every month t of the excess returns ($R^e_{n,t} = R_{n,t} - R^f_t$) on the n stocks that are in the universe of investable stocks in month t onto a constant and their time t inflation-betas ($\hat{\beta}_{n,t}$) from equation (1) : $R^e_{n,t} = \gamma_t + \lambda_t \hat{\beta}_{n,t} + \varepsilon_t,\ n = 1, ..., N$. To get an estimate of the market price of inflation risk for pro-/countercyclical inflation states separately, I run the Fama and MacBeth (1973) regression by only considering the months t for which the signal indicates pro-/countercyclical inflation states. The resulting estimates $\hat{\gamma}_t$ and $\hat{\lambda}_t$ are averaged over time ($\overline{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t$ and $\overline{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t$). Two-sided p-Values are reported in parentheses.

Fama-MacBeth Cross Sectional Regressions: U.S. 1952-2013						
Signal	**Entire Sample**		**Countercyclical**		**Procyclical**	
	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$	$\overline{\gamma}$	$\overline{\lambda}$
Δ Ind. Prod. - Inflation	0.0073	-0.0001	0.0064	-0.0003	0.0092	0.0002
	(0.0000)	(0.4070)	(0.0035)	(0.0239)	(0.0024)	(0.4756)
Stock - Bond	0.0073	-0.0001	0.0086	-0.0005	0.0064	0.0001
	(0.0000)	(0.4070)	(0.0023)	(0.0049)	(0.0047)	(0.5665)

A.4 UK - 1980-2013: Robustness

A.4.1 Signal: Real GDP Growth - Inflation Correlations

Table XVI. Returns on Signal-Based Strategy for Alternative Signal Specifications, UK $1980-2013$**.** This Table reports the profitability of the signal-based long-short strategy when the strategy is implemented using k quarters of data to calculate the rolling correlations between yearly real GDP growth and yearly inflation, with k ranging from 12 to 61 quarters. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors and 2-sided p-values from Newey-West standard errors using 6 lags are reported. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

	CAPM		FF		CAR			CAPM		FF		CAR	
Lag	α	P-Value	α	P-Value	α	P-Value	**Lag**	α	P-Value	α	P-Value	α	P-Value
12	0.0007	0.799	0.0001	0.9613	(0.0007)	0.8422	**37**	0.0046	0.1207	0.0053	0.0712*	0.0070	0.0305**
13	0.0012	0.6732	0.0006	0.8384	(0.0001)	0.9747	**38**	0.0046	0.1207	0.0053	0.0712*	0.0070	0.0305**
14	0.0027	0.3452	0.0020	0.499	0.0007	0.8299	**39**	0.0044	0.131	0.0051	0.0781*	0.0068	0.0358**
15	0.0035	0.2298	0.0026	0.3598	0.0014	0.6903	**40**	0.0046	0.1192	0.0053	0.0718*	0.0069	0.033**
16	0.0027	0.3582	0.0020	0.4978	0.0006	0.8723	**41**	0.0036	0.2205	0.0044	0.1375	0.0065	0.044**
17	0.0021	0.4781	0.0017	0.5754	0.0009	0.8089	**42**	0.0039	0.1859	0.0045	0.1253	0.0066	0.0417**
18	0.0028	0.3413	0.0024	0.4321	0.0016	0.654	**43**	0.0039	0.1857	0.0044	0.1391	0.0070	0.0275**
19	0.0026	0.3936	0.0021	0.4912	0.0016	0.6544	**44**	0.0041	0.1541	0.0047	0.1116	0.0073	0.0192**
20	0.0014	0.6383	0.0011	0.7361	0.0009	0.8134	**45**	0.0064	0.0411**	0.0069	0.0222**	0.0102	0.003***
21	0.0017	0.5817	0.0012	0.6995	0.0009	0.7921	**46**	0.0066	0.0351**	0.0071	0.019**	0.0104	0.0023***
22	0.0021	0.4885	0.0016	0.6061	0.0013	0.7198	**47**	0.0067	0.0325**	0.0072	0.0169**	0.0105	0.0021***
23	0.0019	0.521	0.0014	0.6563	0.0007	0.8431	**48**	0.0063	0.0434**	0.0069	0.0235**	0.0101	0.0032***
24	0.0028	0.3507	0.0023	0.4579	0.0018	0.6201	**49**	0.0063	0.045**	0.0068	0.0244**	0.0100	0.0037***
25	0.0011	0.7181	0.0005	0.8751	0.0002	0.9568	**50**	0.0043	0.1396	0.0048	0.1035	0.0078	0.0106**
26	0.0017	0.5699	0.0014	0.6584	0.0017	0.6404	**51**	0.0060	0.0596*	0.0065	0.0333**	0.0096	0.0057***
27	0.0021	0.4883	0.0018	0.572	0.0022	0.5483	**52**	0.0058	0.07*	0.0063	0.04**	0.0093	0.0072***
28	0.0017	0.5606	0.0014	0.6637	0.0019	0.5856	**53**	0.0058	0.0683*	0.0063	0.0404**	0.0093	0.008***
29	0.0010	0.7502	0.0007	0.8447	0.0010	0.7906	**54**	0.0055	0.0831*	0.0060	0.0508*	0.0091	0.0097***
30	0.0039	0.1282	0.0045	0.0814*	0.0042	0.1823	**55**	0.0055	0.0825*	0.0060	0.0506*	0.0091	0.0095***
31	0.0048	0.0778*	0.0055	0.0444**	0.0055	0.0702*	**56**	0.0053	0.0981*	0.0058	0.0625*	0.0090	0.0103**
32	0.0060	0.0449**	0.0065	0.0341**	0.0075	0.0332**	**57**	0.0059	0.0637*	0.0064	0.0367**	0.0097	0.0053***
33	0.0049	0.0803*	0.0054	0.0621*	0.0061	0.0647*	**58**	0.0055	0.0831*	0.0061	0.0474**	0.0094	0.0067***
34	0.0041	0.1609	0.0047	0.1016	0.0052	0.1317	**59**	0.0055	0.0865*	0.0060	0.0483**	0.0093	0.007***
35	0.0034	0.2598	0.0042	0.1422	0.0061	0.0539*	**60**	0.0058	0.0688*	0.0063	0.036**	0.0097	0.0048***
36	0.0042	0.1552	0.0049	0.0885*	0.0066	0.039**	**61**	0.0057	0.0729*	0.0063	0.038**	0.0097	0.0047***

Table XVII. Returns on Inflation-Beta Based Strategies II, $k = 36$, UK 1980 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation-betas. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0011	0.0005	0.0000	0.0005	0.0007	0.0047	0.0056	0.0050	0.0036	0.0043
	(0.7086)	(0.8441)	(0.9898)	(0.8386)	(0.7814)	(0.1152)	(0.0445)	(0.0599)	(0.1607)	(0.0874)
CAPM Alphas	0.0012	0.0008	0.0002	0.0006	0.0006	0.0042	0.0053	0.0049	0.0036	0.0044
	(0.7032)	(0.7875)	(0.9354)	(0.8191)	(0.8263)	(0.1552)	(0.0466)	(0.0565)	(0.1334)	(0.0781)
FF Alphas	0.0021	0.0015	0.0009	0.0010	0.0009	0.0049	0.0061	0.0059	0.0046	0.0053
	(0.5126)	(0.6212)	(0.7537)	(0.6888)	(0.7162)	(0.0885)	(0.0205)	(0.0202)	(0.0581)	(0.0283)
Carhart Alphas	0.0024	0.0014	0.0004	0.0008	0.0007	0.0066	0.0070	0.0055	0.0033	0.0037
	(0.5580)	(0.7152)	(0.8949)	(0.7668)	(0.8044)	(0.0390)	(0.0200)	(0.0477)	(0.1810)	(0.1398)
Sharpe Ratio	0.07	0.03	0.00	0.04	0.05	0.28	0.36	0.33	0.25	0.30
	(0.7426)	(0.8639)	(0.9907)	(0.8425)	(0.7891)	(0.1097)	(0.0395)	(0.0629)	(0.1585)	(0.0923)

A.4.2 Signal: Industrial Production Growth - Inflation Correlations

Table XVIII. Returns on Signal-Based Strategy for Alternative Signal Specifications, UK $1980-2013$. This Table reports the profitability of the signal-based long-short strategy when the strategy is implemented using k months of data to calculate the rolling correlations between yearly industrial production growth and yearly inflation, with k ranging from 34 to 180 months. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation-betas $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors and 2-sided p-values from Newey-West standard errors using 6 lags are reported. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

	CAPM		FF		CAR			CAPM		FF		CAR	
Lag	α	P-Value	α	P-Value	α	P-Value	**Lag**	α	P-Value	α	P-Value	α	P-Value
34	0.0010	0.7352	0.0008	0.787	0.0019	0.6147	**108**	0.0061	0.0552*	0.0068	0.022**	0.0087	0.0185**
36	0.0016	0.5963	0.0013	0.6551	0.0024	0.5168	**110**	0.0061	0.0552*	0.0068	0.022**	0.0087	0.0185**
38	0.0024	0.4092	0.0020	0.4792	0.0028	0.4457	**112**	0.0057	0.0686*	0.0065	0.0291**	0.0083	0.0246**
40	0.0012	0.6727	0.0009	0.7429	0.0021	0.5569	**114**	0.0058	0.0656*	0.0065	0.028**	0.0084	0.0231**
42	0.0028	0.3411	0.0024	0.3923	0.0032	0.386	**116**	0.0058	0.0656*	0.0065	0.028**	0.0084	0.0231**
44	0.0030	0.2942	0.0026	0.3371	0.0034	0.3511	**118**	0.0058	0.066*	0.0065	0.0282**	0.0084	0.0233**
46	0.0022	0.4353	0.0018	0.5206	0.0027	0.4554	**120**	0.0058	0.066*	0.0065	0.0282**	0.0084	0.0233**
48	0.0005	0.8674	0.0002	0.9554	0.0012	0.7537	**122**	0.0055	0.0787*	0.0062	0.0367**	0.0082	0.0255**
50	0.0018	0.5352	0.0015	0.5916	0.0024	0.4967	**124**	0.0058	0.0641*	0.0065	0.0276**	0.0084	0.0226**
52	0.0028	0.3481	0.0026	0.3699	0.0031	0.415	**126**	0.0064	0.0507*	0.0071	0.0205**	0.0089	0.02**
54	0.0018	0.5366	0.0015	0.6208	0.0028	0.4381	**128**	0.0052	0.1048	0.0060	0.0475**	0.0082	0.0254**
56	0.0023	0.46	0.0019	0.533	0.0033	0.3747	**130**	0.0052	0.1084	0.0059	0.0496**	0.0082	0.0261**
58	0.0011	0.7131	0.0008	0.7996	0.0023	0.5345	**132**	0.0057	0.071*	0.0064	0.0332**	0.0086	0.0207**
60	0.0011	0.7137	0.0007	0.8319	0.0022	0.5567	**134**	0.0054	0.089*	0.0061	0.0446**	0.0083	0.0249**
62	0.0010	0.7546	0.0006	0.8651	0.0016	0.6751	**136**	0.0060	0.0612*	0.0066	0.0328**	0.0091	0.0125**
64	0.0026	0.386	0.0031	0.2525	0.0020	0.5978	**138**	0.0054	0.0911*	0.0060	0.053*	0.0088	0.0162**
66	0.0043	0.1894	0.0051	0.0941*	0.0054	0.1642	**140**	0.0057	0.0723*	0.0063	0.0393**	0.0091	0.0113**
68	0.0048	0.1477	0.0055	0.077*	0.0066	0.1092	**142**	0.0064	0.0411**	0.0069	0.0222**	0.0102	0.003***
70	0.0052	0.1053	0.0058	0.055*	0.0078	0.0428**	**144**	0.0067	0.0337**	0.0072	0.0182**	0.0105	0.0022***
72	0.0050	0.11	0.0056	0.056*	0.0072	0.0565*	**146**	0.0069	0.0295**	0.0074	0.0156**	0.0106	0.0019***
74	0.0044	0.1605	0.0051	0.0862*	0.0053	0.1786	**148**	0.0067	0.0325**	0.0072	0.0169**	0.0105	0.0021***
76	0.0041	0.1941	0.0047	0.1057	0.0059	0.1198	**150**	0.0065	0.0374**	0.0070	0.0198**	0.0103	0.0025***
78	0.0042	0.1846	0.0050	0.0843*	0.0070	0.0539*	**152**	0.0063	0.0458**	0.0068	0.025**	0.0100	0.0036***
80	0.0039	0.2274	0.0047	0.1087	0.0070	0.0553*	**154**	0.0063	0.045**	0.0068	0.0244**	0.0100	0.0037***
82	0.0040	0.2166	0.0048	0.0996*	0.0071	0.0531*	**156**	0.0059	0.0644*	0.0064	0.0358**	0.0095	0.0058***
84	0.0046	0.1487	0.0053	0.0699*	0.0070	0.0615*	**158**	0.0058	0.0679*	0.0063	0.0378**	0.0095	0.0062***
86	0.0048	0.1302	0.0055	0.0595*	0.0072	0.0547*	**160**	0.0060	0.0596*	0.0065	0.0333**	0.0096	0.0057***
88	0.0052	0.1035	0.0059	0.0486**	0.0075	0.0463**	**162**	0.0058	0.0665*	0.0063	0.0378**	0.0094	0.0067***
90	0.0055	0.0869*	0.0062	0.0392**	0.0079	0.0358**	**164**	0.0055	0.0847*	0.0060	0.0513*	0.0090	0.0106**
92	0.0056	0.0807*	0.0063	0.0347**	0.0081	0.0304**	**166**	0.0058	0.0683*	0.0063	0.0404**	0.0093	0.008***
94	0.0053	0.0947*	0.0061	0.0431**	0.0079	0.0361**	**168**	0.0056	0.0813*	0.0060	0.0493**	0.0091	0.0094***
96	0.0055	0.0821*	0.0063	0.0357**	0.0081	0.0303**	**170**	0.0056	0.0785*	0.0061	0.0475**	0.0092	0.0088***
98	0.0061	0.0542*	0.0068	0.0211**	0.0087	0.0185**	**172**	0.0055	0.0825*	0.0060	0.0506*	0.0091	0.0095***
100	0.0061	0.0538*	0.0068	0.0215**	0.0088	0.0181**	**174**	0.0055	0.0862*	0.0060	0.0539*	0.0091	0.0091***
102	0.0059	0.0627*	0.0066	0.0253**	0.0085	0.023**	**176**	0.0055	0.0839*	0.0060	0.0514*	0.0091	0.0079***
104	0.0061	0.0552*	0.0068	0.022**	0.0087	0.0185**	**178**	0.0063	0.0541*	0.0069	0.0287**	0.0100	0.0053***
106	0.0061	0.0552*	0.0068	0.022**	0.0087	0.0185**	**180**	0.0053	0.0958*	0.0059	0.0556*	0.0088	0.0131**

Table XIX. Returns on Inflation-Beta Based Strategies II, $k = 108$, UK 1980 − 2013. This Table reports the profitability of two inflation-beta based long-short strategies. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent 1 to 12 months. The **unconditional inflation-beta strategy** goes long portfolio 1 and short portfolio 10. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period) and the overlapping portfolio approach of Jegadeesh and Titman (1993) is used to calculate the monthly returns. Time-series means, annualized Sharpe ratios plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported for holding periods of 1, 3, 6, 9 and 12 months. 2-sided p-values from Newey-West standard errors using 6 lags are given in parentheses.

	Unconditional Strategy					**Signal-Based Strategy**				
Holding	1	3	6	9	12	1	3	6	9	12
Panel 1: Summary Statistics - Long Leg MINUS Short Leg										
TS Mean	0.0011	0.0005	0.0000	0.0005	0.0007	0.0064	0.0069	0.0053	0.0036	0.0040
	(0.7086)	(0.8441)	(0.9898)	(0.8386)	(0.7814)	(0.0316)	(0.0130)	(0.0457)	(0.1581)	(0.1088)
CAPM Alphas	0.0012	0.0008	0.0002	0.0006	0.0006	0.0061	0.0068	0.0052	0.0036	0.0040
	(0.7032)	(0.7875)	(0.9354)	(0.8191)	(0.8263)	(0.0552)	(0.0199)	(0.0474)	(0.1377)	(0.1028)
FF Alphas	0.0021	0.0015	0.0009	0.0010	0.0009	0.0068	0.0076	0.0063	0.0046	0.0050
	(0.5126)	(0.6212)	(0.7537)	(0.6888)	(0.7162)	(0.0220)	(0.0063)	(0.0140)	(0.0540)	(0.0374)
Carhart Alphas	0.0024	0.0014	0.0004	0.0008	0.0007	0.0087	0.0087	0.0060	0.0036	0.0037
	(0.5580)	(0.7152)	(0.8949)	(0.7668)	(0.8044)	(0.0185)	(0.0119)	(0.0371)	(0.1503)	(0.1395)
Sharpe Ratio	0.07	0.03	0.00	0.04	0.05	0.38	0.44	0.35	0.25	0.28
	(0.7426)	(0.8639)	(0.9907)	(0.8425)	(0.7891)	(0.0379)	(0.0171)	(0.0534)	(0.1587)	(0.1129)

A.4.3 Signal: Stock - Bond Correlations

Table XX. Returns on Signal-Based Strategy for Alternative Signal Specifications, UK 1980 − 2013. This Table reports the profitability of the signal-based long-short strategy when the strategy is implemented using k months of data to calculate the (smoothed) rolling correlations between monthly series of yearly stock and bond returns, with k ranging from 34 to 180 months. At the end of each month t, I sort the investable stocks into 10 portfolios according to their inflation betays $\hat{\beta}_{n,t}$ at time t. Portfolio 1 (10) contains the stocks with the lowest (highest) inflation betays. I then calculate value-weighted returns on the ten portfolios over the subsequent month. The **signal-based strategy** goes long portfolio 1 (10) and short portfolio 10 (1) if the signal at the end of month t signal indicates that inflation is countercyclical (procyclical). The respective positions are held from month t to $t+1$ and the portfolios are rebalanced monthly. Alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors and 2-sided p-values from Newey-West standard errors using 6 lags are reported. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

	CAPM		FF		CAR			CAPM		FF		CAR	
Lag	α	P-Value	α	P-Value	α	P-Value	**Lag**	α	P-Value	α	P-Value	α	P-Value
34	0.0046	0.1408	0.0052	0.0809*	0.0071	0.0559*	**108**	0.0058	0.0658*	0.0064	0.0334**	0.0098	0.0042***
36	0.0061	0.0545*	0.0068	0.0223**	0.0087	0.0201**	**110**	0.0059	0.0637*	0.0065	0.0322**	0.0098	0.0041***
38	0.0056	0.0779*	0.0063	0.0363**	0.0085	0.0215**	**112**	0.0049	0.1259	0.0054	0.0814*	0.0087	0.0111**
40	0.0054	0.089*	0.0061	0.0446**	0.0083	0.0249**	**114**	0.0050	0.1179	0.0055	0.0752*	0.0089	0.0097***
42	0.0054	0.0892*	0.0060	0.0519*	0.0088	0.0158**	**116**	0.0054	0.0912*	0.0058	0.0542*	0.0092	0.0066***
44	0.0054	0.0897*	0.0060	0.052*	0.0088	0.016**	**118**	0.0053	0.0952*	0.0058	0.057*	0.0092	0.0067***
46	0.0060	0.0553*	0.0066	0.0287**	0.0098	0.0044***	**120**	0.0058	0.073*	0.0063	0.0399**	0.0095	0.0058***
48	0.0064	0.0411**	0.0069	0.0222**	0.0102	0.003***	**122**	0.0053	0.0929*	0.0058	0.0573*	0.0086	0.0136**
50	0.0067	0.0337**	0.0072	0.0182**	0.0105	0.0022***	**124**	0.0047	0.1373	0.0051	0.096*	0.0076	0.0351**
52	0.0069	0.0295**	0.0074	0.0156**	0.0106	0.0019***	**126**	0.0049	0.1216	0.0053	0.0776*	0.0077	0.0327**
54	0.0067	0.0325**	0.0072	0.0169**	0.0105	0.0021***	**128**	0.0051	0.1094	0.0056	0.0687*	0.0079	0.0302**
56	0.0065	0.0374**	0.0070	0.0198**	0.0103	0.0025***	**130**	0.0037	0.2129	0.0041	0.1657	0.0063	0.0542*
58	0.0063	0.0458**	0.0068	0.025**	0.0100	0.0036***	**132**	0.0036	0.2211	0.0040	0.1731	0.0061	0.0587*
60	0.0062	0.0498**	0.0067	0.0276**	0.0099	0.0041***	**134**	0.0023	0.4604	0.0034	0.2756	0.0027	0.4792
62	0.0061	0.0543*	0.0066	0.0297**	0.0098	0.0047***	**136**	0.0021	0.5071	0.0032	0.311	0.0024	0.5437
64	0.0059	0.0644*	0.0064	0.0358**	0.0095	0.0058***	**138**	0.0020	0.523	0.0031	0.3236	0.0023	0.5618
66	0.0058	0.0679*	0.0063	0.0378**	0.0095	0.0062***	**140**	0.0016	0.6148	0.0028	0.3886	0.0019	0.6367
68	0.0060	0.057*	0.0065	0.0317**	0.0096	0.0054***	**142**	0.0019	0.5644	0.0029	0.3665	0.0020	0.6135
70	0.0059	0.0606*	0.0065	0.0338**	0.0096	0.0058***	**144**	0.0018	0.5801	0.0028	0.38	0.0020	0.6289
72	0.0058	0.0665*	0.0063	0.0378**	0.0094	0.0067***	**146**	0.0012	0.7005	0.0022	0.4971	0.0013	0.7563
74	0.0055	0.0847*	0.0060	0.0513*	0.0090	0.0106**	**148**	0.0012	0.71	0.0022	0.5059	0.0012	0.7652
76	0.0059	0.0614*	0.0064	0.0358**	0.0094	0.0071***	**150**	0.0012	0.7015	0.0022	0.498	0.0013	0.7568
78	0.0058	0.0665*	0.0063	0.0391**	0.0093	0.0077***	**152**	0.0012	0.7015	0.0022	0.498	0.0013	0.7568
80	0.0055	0.0831*	0.0060	0.0508*	0.0091	0.0097***	**154**	0.0011	0.7264	0.0021	0.5215	0.0012	0.7782
82	0.0056	0.0785*	0.0061	0.0475**	0.0092	0.0088***	**156**	0.0009	0.7881	0.0018	0.5778	0.0011	0.7898
84	0.0055	0.0825*	0.0060	0.0506*	0.0091	0.0095***	**158**	0.0009	0.7881	0.0018	0.5778	0.0011	0.7898
86	0.0055	0.0862*	0.0060	0.0539*	0.0091	0.0091***	**160**	0.0018	0.5878	0.0026	0.4167	0.0018	0.6648
88	0.0056	0.0773*	0.0061	0.0458**	0.0093	0.0075***	**162**	0.0014	0.6757	0.0022	0.4986	0.0012	0.7657
90	0.0059	0.0637*	0.0064	0.0367**	0.0097	0.0053***	**164**	0.0014	0.6757	0.0022	0.4986	0.0012	0.7657
92	0.0055	0.0832*	0.0060	0.0483**	0.0093	0.007***	**166**	0.0017	0.6137	0.0025	0.4413	0.0016	0.7022
94	0.0055	0.0831*	0.0061	0.0474**	0.0094	0.0067***	**168**	0.0011	0.7333	0.0019	0.547	0.0011	0.7909
96	0.0053	0.0953*	0.0059	0.054*	0.0092	0.0075***	**170**	0.0012	0.699	0.0021	0.5146	0.0012	0.761
98	0.0054	0.0897*	0.0060	0.0505*	0.0093	0.0075***	**172**	0.0012	0.699	0.0021	0.5146	0.0012	0.761
100	0.0055	0.0824*	0.0061	0.0451**	0.0094	0.0063***	**174**	0.0008	0.8112	0.0016	0.612	0.0010	0.8072
102	0.0059	0.0619*	0.0065	0.0318**	0.0098	0.0041***	**176**	0.0008	0.8112	0.0016	0.612	0.0010	0.8072
104	0.0057	0.0729*	0.0063	0.038**	0.0097	0.0047***	**178**	0.0006	0.8618	0.0014	0.6564	0.0009	0.8316
106	0.0060	0.0609*	0.0066	0.0305**	0.0100	0.0036***	**180**	0.0002	0.9547	0.0010	0.748	0.0005	0.8961

Media Coverage, the Cross-Section of Stock Returns and Market States: An International Study

Dominic Burkhardt* Nilufer Caliskan

Abstract

Employing data on mass media coverage provided by Bloomberg News Trend, we analyze the relation between mass media coverage and the cross-section of stock returns in 20 financially developed stock markets around the world. We find considerable differences as to the magnitude and direction of this relation across countries. Analyzing the relation between media coverage and stock returns conditional on the market state, we find that in most countries stocks not covered by mass media during bull markets subsequently clearly outperform stocks that are highly covered in bull markets. In bear markets on the other hand, the return differential between stocks not covered by mass media and stocks highly covered by mass media is mostly insignificant or negative. A strategy that goes long (short) stocks not covered and short (long) those highly covered by mass media when the market state is good (bad), yields a positive return premium in 16 out of 20 countries. This return premium is highly significant and persistent in the countries with the largest stock markets.

KEYWORDS: news effect, media coverage, cross-section of stock returns, market states

*We would like to thank thank Henrik Hasseltoft, Thorsten Hens, Jens Jackwerth, Alexandre Ziegler and seminar participants at the University of Zurich for valuable input and helpful comments.

1 Introduction

Publicly available news announcements are an important channel for disseminating information to investors. Every day, thousands of articles about companies are published in mass media and processed by investors in order to assess their potential impact on changes in firm values.

By examining whether mass media coverage affects the cross-section of stock returns in the U.S., Fang and Peress (2009) shed light on an important aspect of the relation between media and stock markets. They count the monthly number of articles published about the stocks in their sample in four influential daily newspapers with nationwide circulation. Based on this number of articles they form three portfolios consisting of stocks that have no-, low- and high-media coverage and evaluate their returns. They find that stocks not covered by mass media earn significantly higher future returns than stocks that are highly covered by mass media, even after controlling for widely accepted risk characteristics. The resulting return premium (called media effect or no-media premium) is of an economically significant magnitude. The media effect is strongest among small illiquid stocks and among stocks with otherwise poor information dissemination. We think that the ability to predict future returns using such a simple measure of news coverage - and hereby completely ignoring the content of the news - is very interesting and worth deepening, especially given that there has been little attempt to quantify the importance of mass media coverage internationally.

In this study, we build on Fang and Peress (2009) and contribute to the literature along four dimensions. First of all, we employ a new measure of mass media coverage, obtained from the Bloomberg News Trend database, also comprising internet news sources. Second, we consider a more recent and longer time period and analyze the media effect for a larger set of U.S. stocks.[1] Using our media coverage measure, we find U.S. results that are qualitatively similar to those of Fang and Peress (2009). Stocks neglected by mass media earn a statistically significant and economically important return premium compared to stocks highly covered by mass media. For portfolio formation and holding periods beyond a horizon of one month, the media effect we find in the U.S. is even stronger than in Fang and Peress (2009). The effect is strongest among the

[1] Our sample period is 1999 to 2012 and we consider all NYSE and NASDAQ stocks. Fang and Peress (2009) consider all NYSE plus 500 randomly selected NASDAQ stocks from 1993 to 2002.

most illiquid set of stocks.

Third, we expand the analysis to an international level by analyzing the entire stock markets in 19 major European and Asia-Pacific (APAC) countries. We employ 12 years of mass media data on more than $21'000$ companies. This large set of international mass media coverage data allows an extensive investigation of the role of mass media coverage in stock pricing. We find considerable differences as to the magnitude and direction of the media effect in countries outside the U.S. Despite the effect being positive in the majority of countries[2], only seven countries (Hongkong, France, Switzerland, Spain, the Netherlands, Belgium and Austria) display positive no-media premiums that are statistically significant and economically large. In the UK we find a large and significant negative no-media premium; returns monotonically increase with media coverage. Despite these heterogeneous country-results, we show that the positive media effect consistently exists and is particularly strong in most countries among specific subgroups of stocks. Especially among small and illiquid stocks, the media effect seems to be a worldwide phenomenon that is of an economically relevant magnitude. Hence, the role of mass media seems to be particularly important for these subsets of stocks, which arguably are characterized by rather poor information dissemination.

And fourth, as our main contribution, we relate the media effect to a simple measure of the state of the market. Defining the market state in a country as good/bullish (bad/bearish) when the fraction of stocks with positive returns in a month is above (below) 50%, we show that in the overwhelming majority of countries, portfolios containing stocks that are not covered by mass media during good market state months subsequently clearly outperform portfolios containing stocks that are highly covered during good market months. Hence, there is a positive, mostly economically large no-media premium, when we condition on the market state being good. Conditional on the market state being bearish on the other hand, we find much smaller and mostly insignificant or negative no-media premiums. Utilizing this insight, we show that a strategy that goes long stocks not covered and short those highly covered by mass media when the market state is good, and the opposite when the market state is bad, yields a positive return premium in 16 out of 20 countries. The premiums are mostly statistically significant, especially

[2]The effect is positive in 14 out of 20 countries.

among the countries with the largest stock market capitalizations in our sample. For these countries, the return premiums are significant for holding periods up to 12 months and stable across various subgroups of stocks.

Since the end of the 1990's the relation between media and stock markets has gained progressively more attention among academics and financial professionals. One strand of literature focuses on individual investors and finds that they are more likely to buy stocks that have attracted their attention. Grullon, Kanatas, and Weston (2004) establish that firms with larger advertising expenditures have a larger number of individual and institutional investors and more liquid stocks, because investors are more likely to buy companies they know and the advertising increases investors' familiarity with the company. Meschke (2004) finds that stocks experience a strong market reaction to CEO interviews on CNBC: First a run-up over three days and then a reversal of similar magnitude during the 10 trading days after the interviews. They show that individual investors are net buyers on the interview days, causing the price run-up. Moreover, Frieder and Subrahmanyam (2005) document that individual investors prefer to invest in firms with easily recognized products and strong brand. Barber and Odean (2008) show that individual investors are net buyers of attention-grabbing stocks, such as e.g. stocks in the news. These stocks catch individual investors' attention and determine their choice set. Using the same retail investor trading data as Barber and Odean (2008), Engelberg and Parsons (2011) find that local media coverage increases the trading activity of retail investors and - to the contrary of the findings of Barber and Odean (2008) - that buying, as well as selling activity increases.[3] Tetlock (2011) test whether investors appropriately distinguish between new and stale firm news and concludes that individual investors overreact to stale information, which then leads to return reversals.[4]

A second strand of literature focuses on over-/underreaction to news and - in condensed form - concludes that price signals with (without) concurrent news give rise to continuation (reversal) patterns. Using headline news data from Dow Jones Newswire, Chan (2003) e.g. finds that stocks with low returns and concurrent headline news in a given month display a negative drift for up to 12 months, whereas stocks with low returns and no concurrent headline news in a

[3]However, the increase in selling activity is less pronounced relative to the increase in buying activity.
[4]Tetlock (2011) defines staleness of news in terms of textual similarity to previous stories about the firm.

given month tend to reverse in the subsequent month. Using DJ newswire and Wall Street Journal stories about U.S. firms, Tetlock (2010) tests predictions from a theoretical model in which public news resolves information asymmetries between informed and uninformed traders. As Chan (2003), Tetlock (2010) finds that stock returns reverse only when the initial price move has no concurrent firm news.

Antweiler and Fank (2004) look at a sample of 45 U.S. companies and count messages posted on Internet stock message boards (Yahoo!Finance and Raging Bull) and use linguistic methods to determine the bullishness of messages. They show that stock messages predict volatility at daily frequencies and also within the trading day, but that their effect on returns is economically small. Tetlock (2007) and Tetlock, Saar-Tschansky, and Macskassy (2008) also analyze the qualitative verbal content of mass media articles about specific companies. Tetlock (2007) shows that high media pessimism predicts downward pressure on aggregate market prices and a subsequent reversal and that unusually high/low media pessimism leads to temporarily high market trading volume. Tetlock, Saar-Tschansky, and Macskassy (2008) find that the fraction of negative words used in firm-specific news articles predicts firm earnings in the next quarter negatively.

The rest of the paper is organized as follows: We review the literature implying testable hypotheses with respect to the relation of mass media coverage and the cross-section of stock returns in Section 2. In Section 3 we explain our methodology and describe our data. Section 4 contains our results. In Subsections 4.1 for the U.S., and 4.2 internationally, we discuss results from forming portfolios based on our media coverage measure. The media premium conditional on market states is analyzed in Subsection 4.3. Section 5 eventually concludes. Additional results and details are presented in the Appendix.

2 Hypotheses Development

In this part of the article we develop hypotheses concerning the relation of mass media coverage and stock returns. In Section 2.1 we discuss hypotheses regarding the unconditional relation between mass media coverage and the cross-section of stock returns. Section 2.2 contains hypotheses suggesting that the relation between media coverage and stock returns depends on market states.

2.1 Unconditional Return Differentials for No- vs. High-Coverage Stocks

The Efficient Market Hypothesis (EMH) in its' semi-strong form posits that it should not be possible to earn abnormal returns by trading based on publicly available information. According to the EMH prices react immediately to new information and almost instantaneously fully reflect all publicly available information. Hence, there is no role for media coverage (which represents publicly available, stale information) within the framework of the EMH. Therefore we posit the following hypothesis:

(H1) *Whether a stock has more or less media coverage should not allow any inference on the stocks' future return, and there is no reason to expect a systematic return difference between stocks covered and those not covered by mass media.*

Nevertheless, there are rational frameworks that exhibit channels through which media coverage could affect future stock returns. One such framework is the "investor recognition hypothesis" of Merton (1987). Merton (1987) models a two-period economy in which investors are not informed about all securities. He argues that investors only follow a subset of stocks because they "must pay a significant set-up cost before they can process detailed information released from time to time about the firm..."(Merton (1987), *p*.489).[5] As a consequence, agents only invest in the subset[6] of stocks they know about, are hence imperfectly diversified and require a premium for bearing idiosyncratic risk. The model implies a shadow cost of not knowing a stock[7] that depends on the shareholder base, relative market size and idiosyncratic volatility. This shadow cost - ceteris paribus - implies higher current prices and lower future expected returns on stocks with a larger investor base (higher investor recognition).[8] Hence, in such an economy, stocks with lower investor recognition yield a return premium relative to stocks with

[5]In the Merton (1987) model, this set-up cost channel is not explicitly modeled, but serves as a qualitative motivation for why investors only know about subsets of companies.
[6]These subsets differ across investors.
[7]Resulting from the Kuhn-Tucker condition of no investment in that particular stock.
[8]The marginal absolute effect of the investor base on this return premium increases with idiosyncratic volatility and relative firm size. For stocks with low idiosyncratic volatility and/or relative size, the marginal effect of the investor base can be very small.

higher investor recognition. On *p*.500, Merton (1987) states that "... a newspaper or other mass media story about the firm or its industry that reaches a large number of investors who are not currently shareholders, could induce some of this number to incur the set-up costs and follow the firm. Having done so, in our model, these investors would evaluate the detailed information about the firm, become new shareholders, and the value of the firm would rise." This statement by Merton suggests that mass media coverage could in fact broaden investor recognition. From this it follows that stocks highly covered by mass media are expected to earn lower future returns than those neglected by mass media. Hence, as Fang and Peress (2009), we hypothesize that:

(H2) *A strategy going long stocks with no-media coverage and short those with high-media coverage should yield a positive return premium on average.*

Other frameworks that hint a role for media coverage are rooted in the large body of literature that aims at modeling information asymmetries in financial markets. In these models, some portion of investors trade based on private information, while the others only trade after the news becomes public. Along these lines, e.g. Tetlock (2010) argues that the dissemination of public news can affect stock returns, as it supports the resolution of private information. Tetlock (2010) models a three-period economy with two groups of investors. In period 1, informed investors observe a private signal and trade on it. A good (bad) signal yields positive (negative) returns in period 1. In period 2, public news reveals the signal to uninformed investors and they trade on it, resulting in positive (negative) return continuation after a good (bad) signal. This return continuation implies higher autoregressive return predictability following news events. Tetlock (2010) also argues that for stocks without news coverage there is no resolution of private information and hence they are more likely to exhibit reversal.[9] Moreover, the model implies that after the private news get resolved through public news, the impact of news on the prices reduces and it is expected that continuation diminishes over time. If one proxies the unobservable good/bad private signals - as Tetlock (2010) in the empirical part does - by positive/negative realized returns, this implies that winning (losing) stocks with concurrent news are expected to continue winning (losing), whereas winning (losing) stocks without media coverage are more likely to reverse. Hence:

(H3) *A strategy being long winner (loser) stocks with no-media coverage and short winner (loser)*

[9]Due to the low autoregressive return predictability generally observed in stock returns.

stocks with high-media coverage should yield a negative (positive) return premium.

Both, Tetlock (2010) and Chan (2003) provide empirical evidence supporting this prediction:[10] They find that stock returns reverse only when the initial price move has no concurrent firm news, and that there is a drift if there is accompanying news. Most importantly with respect to our study, Chan (2003) finds that stocks with low returns and concurrent headline news in a given month display a negative drift for up to 12 months, whereas stocks with low returns and no concurrent headline news in a given month tend to reverse in the subsequent month. For stocks with high returns and concurrent news, he finds less drift.

Citing p.2010 of Fang and Peress (2009) that refers to the findings of Chan (2003): "These patterns could generate the result that no-coverage stocks have higher returns than high-coverage stocks, to the extent that no-coverage stocks correspond to "no news stocks" and high-coverage stocks to "news-stocks". In this case, our long-short strategy will be equivalent to buying no-news stocks and shorting news stocks, and given the reversal among no-news stocks (losers in particular) and drift among news stocks (losers in particular), such a strategy would generate a positive alpha, consistent with our results. Since the reversal and drift effects documented in Chan (2003) are concentrated among losers, there is concern that our results represent the same drift/reversal patterns, ..." Thus, we posit that:

*(**H4**) If winning (losing) stocks with concurrent news continue winning (losing) and winning/losing stocks without media coverage reverse, and if the effect among losers is stronger than among winners, this can yield positive return differentials between no-media versus high-media coverage stocks.*

Finally, the findings by Barber and Odean (2008), Engelberg and Parsons (2011) and others, reviewed in the introduction, suggest that individual investors exhibit behavioral biases and direct their attention to stocks that are in the media. If individual investors are net-buyers of stocks that are in the news and, as Barber, Odean, and Zhu (2009) show, temporarily inflate these stock's prices which then leads to a subsequent reversal, then we would also expect a positive return differential between stocks with no-media coverage and stocks with high-media

[10] Chan (2003) has no formal model. He relates his findings to the under-/overreaction hypothesis of Jegadeesh and Titman (1993) and interprets them to mean that investors underreact to public news, resulting in a drift and overreact to price movements unaccompanied by news (spurious price movements), resulting in a reversal.

coverage. This return differential should then be largely driven by the negative returns on high coverage stocks.

2.2 Conditional Return Differentials for No- vs. High-Coverage Stocks based on the Market State

The key argument/channel needed to derive from the Merton (1987) model the hypothesis that no-media coverage stocks should on average outperform high-media coverage stocks, is that mass media coverage reaches many investors that are not current shareholders and induces some of these investors to incur the set-up costs to follow the firm and to eventually become new shareholders. Despite mass media coverage reaching many investors that are not current shareholders during good, as well as during bad market states, we think it is reasonable/intuitive to posit that during bad market states, this coverage induces less investors to actually incur the set-up costs to follow the firm and even fewer of them to actually become new shareholders. First of all, worse economic conditions may reduce the willingness of investors to incur any (set-up) costs. Secondly, firm news are presumably rather bad on average during bad market states, hereby reducing the incentive to eventually become a new shareholder. If this is the case, we would expect that:

(H5) *The media effect is significantly more pronounced during good, than during bad market states.*

Merton (1987) points out that a proper consideration of the channel from high mass media coverage to an increase in the shareholder base requires a dynamic version of his model. And he also explicates how such a model could look. Citing Merton (1987), *p*.500: "In such a model, current (informed) shareholders of firm k would have expectations about the future time path of the shareholder base. If a favorable story implies an upward revision in those anticipations, then the price should rise immediately, ... Similarly, an unfavorable story implying a reduction in the anticipated growth in the investor base should cause an immediate price decline." Assuming that firm news are good (bad) on average during good (bad) market states, the dynamic model that Merton sketches also implies that a larger no-media premium should be expected during good market states.

As mentioned, the set-up cost channel is not explicitly modeled in the Merton (1987) model, but serves as a motivation for why investors only know about subsets of companies. But also strictly within the Merton (1987) framework, one can identify channels that suggest a larger no-media premium in good market states. Concretely, the equilibrium aggregate shadow cost (λ_k) of not knowing stock k depends, inter alia, positively on the expected risk-adjusted excess return over the single factor.[11] This shadow cost, which is measured in units of expected return, can be interpreted as the opportunity cost of not investing in stock k. When there is an external shock that reduces the risk adjusted expected excess returns for reasons other than an increase in q_k, this will reduce the shadow cost, and hence the effect of the investor base on stock returns will decrease. If such a negative shock[12] is more likely to occur during bad market states, then this also suggests that a larger no-media premium should be expected during good market states.

Furthermore, it can be shown that the sensitivity of expected returns with respect to changes in the investor base increases when the expected firm cash-flows increase. This is a feature that is more likely to occur during good market states, hereby suggesting a larger no-media premium in good market states.

And yet another channel that suggests a larger no-media premium in good market states could proceed via idiosyncratic volatility. Xu and Malkiel (2003) show that cross-sectionally, companies with high expected earnings growth exhibit higher idiosyncratic volatility. In the Merton (1987) model, the effect of changes in the investor base on return premiums increases with idiosyncratic volatility. Assuming a higher percentage of firms with high expected earnings growth during good market states then implies that a larger no-media premium should be expected during good market states.

The hypothesis (*H5*) deducted from Merton (1987) is at odds with the likely implications of the asymmetric information model of Tetlock (2010) and the findings of Chan (2003), when we reconsider their findings in the context of good/bad market states. If there are proportionally

[11]Formally, $\lambda_k = (1 - q_k)(\bar{R}_k - R - b_k(\bar{R}_{n+1} - R))$, where $\bar{R}_k$, $\bar{R}_{n+1}$, and R denote expected returns on the asset k, on the common factor asset, and on the riskless asset, respectively. q_k denotes the fraction of all investors who know about security k.

[12]E.g. a decrease in expected returns for the stock, increased uncertainty in a market pushing expected market premiums upward and/or increased market risk exposure possibly associated with firms' leverage effects in downturns.

more winners (losers) in good (bad) market states, the continuation and reversal patterns of winners (losers) are expected to dominate (in terms of magnitude and/or significance). This implies the following hypothesis:

(H6) *The return differential for no-news versus high-news stocks is negative (positive) in good (bad) market states.*[13]

Changing no-media premiums conditional on the state of the market would imply that unconditional no-media premiums cannot be of similar magnitudes in different markets, unless these markets go through similar patterns of good/bad market states. Hence, we expect that depending on the heterogeneity of the occurrence of good/bad market states across countries during our sample period, we will find heterogeneous unconditional no-media premiums across different stock markets.

3 Data and Methodology

3.1 Methodology

To evaluate whether there is a systematic return differential between stocks with no- and high-media coverage (*H1* vs. *H2*), we follow the methodology of Fang and Peress (2009). At the end of each month we split our universe of investable stocks in a specific country into three portfolios. The first one (called the no-media coverage portfolio) consists of all the stocks without media coverage (no articles in the Bloomberg News Trend database) during the month. The second portfolio contains the stocks with low-media coverage and the third portfolio the stocks with high-media coverage during the month. To differentiate between low and high coverage stocks we follow Fang and Peress (2009) and use the median number of articles on all stocks that have media coverage in that month. We perform this analysis with media coverage measured over periods ranging from 1 to 12 months (portfolio formation periods). We then calculate equally-weighted returns on the three portfolios over the subsequent 1 to 12 months (portfolio holding

[13]These conjecture only holds if the differences in absolute magnitude of the media effects among winners/losers are not too pronounced.

periods).[14] To examine the existence of a return premium for no-coverage stocks, we construct a zero-investment portfolio that goes long the no-media coverage portfolio and short the high-media coverage portfolio. The resulting time-series of monthly zero-investment portfolio returns is then evaluated against the CAPM, the Fama-French and the Carhart factors. We denote the return premiums resulting from this exercise as our unconditional results. They are presented in Section 4.1 for the U.S. and in Section 4.2.1 for the remaining countries.

To find out whether our unconditional results are possibly driven by the effects in Chan (2003) and Tetlock (2010), we first examine the no-media premium within terciles of stocks formed according to current month returns in Section 4.2.2. This allows us to analyze if the media effects among winner and loser stocks are consistent with the implications stated in Chan (2003) and Tetlock (2010) (*H3*). For the countries in which this is the case, we then check whether the corresponding continuation/reversal patterns potentially cause the unconditional media effect results we find (*H4*).

We also analyze whether there are subgroups of stocks for which the media effect is pronounced and robust across countries. To do so, we first sort all stocks into terciles according to firm characteristics (such as e.g. market capitalization) at the end of each month. Within each of the resulting terciles, we form our usual no-, low- and high-media coverage portfolios and calculate the subsequent returns of the media based long-short strategy. The resulting monthly returns are evaluated against the risk factors. These are our conditional results. They can be found in Section 4.2.3.

The main focus of this article is on the relation between media coverage and the cross-section of stock returns conditional on the state of the market. We consider the market state in a given month and country to be good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. This simple measure of market states focuses on financial market performance rather than market conditions from a general macro-economic perspective. We believe that this provides a more up-to-date/real-time measure of the (perceived) current market state compared to a measure based on slow-changing overall

[14]Fang and Peress (2009) and Chan (2003) also use equally-weighted returns, among others. As e.g. Fang and Peress (2009), Chan (2003) or Fama (1998) we use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns.

economic conditions.[15] In order to evaluate the relation of media coverage and the cross-section of stock returns conditional on the state of the market, we first analyze the no- versus high-coverage strategy returns separately following good and bad market states. Then we apply our simple market state measure as a (out-of-sample) signal on the original long-short strategy. Instead of always being long no-coverage stocks and and short high coverage stocks, we reverse the long- and short-positions by taking a long position on high media coverage stocks and a short position on no-media coverage stocks if the market state is bad at the time we form the portfolios. As for the pure no-high coverage strategy, we evaluate the resulting time-series of monthly strategy returns against the CAPM, the Fama-French and the Carhart factors. The corresponding results are summarized in Section 4.3.

3.2 Data

Our sample consists of all common stocks listed at some point in time from December 1999 to December 2012 on the main local exchanges of 20 developed countries. We only consider primary listings of common stocks. Besides the U.S. market, where we consider all stocks listed on NYSE and NASDAQ, we collect individual equity data of 14 major European and five major Asian countries' stock markets.[16]

Stock returns, prices, market capitalization, trading volume and accounting data are from Bloomberg (BB). All our returns and results reported are in terms of U.S. Dollars. Risk factors (market, size, value, momentum) and risk-free rates for the U.S. and Japan are from Kenneth French's Data Library.[17] Risk factors for the European and APAC countries are either from the CCRS-DBF Risk Factor Database[18] from the Institute of Banking and Finance at the University

[15]Moreover, we avoid problems that may arise when using market returns to proxy the state of the market (as e.g. Cooper, Gutierrez, and Hameed, 2004). Such a measure may indicates positive market states when a few shares outperform drastically, even though a large proportion of the market is subject to losses. Nevertheless, for robustness we also report results based on this measure in the Internet Appendix. The results are qualitatively similar.

[16]The countries considered are the same as in Fama and French (2012). The European countries we consider are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom. These are the largest markets in Europe by market capitalization. See e.g. http://www.quandl.com/economics/stock-market-capitalization-all-countries. From Asia we have Japan and the APAC countries Australia, Hong Kong, New Zealand and Singapore.

[17]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[18]http://www.bf.uzh.ch/cms/publications/risk-factor-database_168_1633.html. For details see Schmidt, Arx, Wagner, and Ziegler (2011).

of Zurich or from Stefano Marmi's Data Library[19]. For Belgium, Denmark, Finland, Greece and New Zealand we could not find publicly available risk factors. In these cases we use the respective regional factors from Kenneth French's Data Library.

Fang and Peress (2009) use the LexisNexis[20] database to get data on a stock's media exposure. They proxy a stock's media coverage by the number of articles published about the stock during a certain month in four major U.S. daily newspapers[21] with nationwide circulation. In order to get this data for each company, the keywords associated with the company name have to be obtained and searched manually in the desired sources. A lot of company names are nomenclatures of localities (e.g. Genolier or Flughafen Zürich) or common names (e.g. Siegfried Holding or Walter Meier AG). This observation, as well as the fact that some companies change their names during the course of our sample period complicates the search for articles about a particular company. This implies that the searches have to be done carefully and that the plausibility of the search results needs to be checked extensively for every single company. Hence, gathering these media coverage data and verifying their plausibility and reliability is a very time-consuming task, which requires a high degree of knowledge about the country, it's stock market and media scene. Given that we have a sample of more than 21′000 companies[22] from 20 countries, this is not a viable way to pursue for us. Instead, we employ "Story Count" data from Bloomberg's News Trend database to get information on a stock's exposure to mass media. Bloomberg's News Trend database collects all articles published in far more than a hundred "top publications globally, which are relevant to financial professionals". These publications not only comprise important national newspapers[23] from all over the world, but also newswires/news tickers and internet sources. The firms can conveniently be identified by their ISIN-number or Bloomberg-ticker and, as in LexisNexis or Factica, it is possible to choose between different levels of "relevance" (high, medium, low) that an article has for the company at hand.[24] Hence, we proxy a stock's monthly media coverage by the number of highly relevant articles that we find in the Bloomberg News Trend database about the stock during a particular month.

[19]http://homepage.sns.it/marmi/Data_Library.html♯datalibrary.
[20]Dow Jones Factiva is an alternative database for the same purpose.
[21]New York Times, USA Today, Wall Street Journal and Washington Post.
[22]Fang and Peress (2009) have a total of about 2000 companies in their sample.
[23]As e.g. Wall Street Journal for the U.S. or Neue Zürcher Zeitung for Switzerland.
[24]Relevance in terms of the match of article content and company.

Of course, our measure of media coverage differs to some extent from a media coverage measure which is solely based on articles published in printed national newspapers as in Fang and Peress (2009). But given the fact that national newspapers from all over the world are an important element of the Bloomberg News Trend database, we expect the two measures to be highly correlated.[25] In order to get an idea about how closely our media coverage measure is related to a measure based on newspaper articles alone, we use the Dow Jones Factiva[26] archive to collect all articles published in seven major Swiss newspapers[27] about 317 Swiss stocks[28] during 2000 to 2009. We use the data to form a media coverage measure in the spirit of Fang and Peress (2009) (number of articles published about each company in each month). We then compare this measure to our Bloomberg Story Count based media coverage. As can be seen in Figure 1 in the Appendix, the correlation between the two measures is indeed reasonably high.

Table I presents summary statistics on our media coverage data across countries. The first column shows the total number of stocks that we consider over the entire sample period for all the countries in our sample. We cover a total of 21′611 companies. Column two contains the average fraction of stocks covered by media (stocks with at least one article) each month. This fraction is highest in the U.S. and, with 67%, of a similar magnitude as the fraction of U.S. stocks covered by the newspaper-based media coverage measure in Fang and Peress (2009) (on average 70% of stocks covered in a year), again indicating that our measure is a good proxy of overall media coverage.[29] For the vast majority of countries, the average fraction of stocks covered each month is in the reasonable range between 30% and 60%. Columns three and four (five and six) provide the mean and median number of articles per month for all stocks (for all stocks that have coverage in a given month). The mean is clearly higher than the median in all cases, indicating that media coverage is skewed in all countries.

To evaluate whether there is a significant return differential between stocks covered and stocks not covered by mass media in a specific country, we follow the approach of Fang and Peress (2009)

[25]Taking into account the increasing emergence of the internet as an important news source during our sample period, we consider it to be reasonable to also include such sources when calculating measures of media coverage.
[26]http://www.dowjones.com/factiva/sources.asp.
[27]Tages Anzeiger, Neue Zürcher Zeitung, Basler Zeitung, Handelszeitung, Finanz und Wirtschaft, Le Temps and Sonntagszeitung. These newspapers account for about 30% of the daily newspaper circulation in Switzerland.
[28]All stocks that were part of the Swiss Performance Index at some point in time during 2000 to 2009.
[29]The same is true for Switzerland if we compare the newspaper-based measure to the Bloomberg Story Count based coverage measure.

Table I. Media Coverage Data - Summary Statistics. This table contains summary statistics on the media coverage data across countries. The total number of stocks considered in each country is given in column one. Column two contains the average of the monthly fraction of stocks with at least one article. Columns three and four (five and six) provide the mean and median number of articles per month for all stocks (for all stocks that have coverage in a given month).

Countries	Total # of stocks	Fraction of Stocks Covered	Mean # articles Total Sample	Median # articles Total Sample	Mean # articles Stocks Covered	Median # articles Stocks Covered
USA	3778	0.67	16	4	22	8
Austria	159	0.38	5	0	13	7
Belgium	252	0.41	5	0	12	6
Denmark	289	0.33	3	0	8	4
Finland	151	0.52	6	2	11	4
France	1366	0.29	5	0	17	4
Germany	1614	0.24	4	0	18	4
Greece	376	0.25	3	0	13	4
Italy	355	0.49	9	0	18	4
Netherlands	214	0.56	12	2	21	6
Norway	339	0.5	5	1	9	4
Spain	221	0.49	9	1	18	6
Sweden	683	0.38	3	0	8	3
Switzerland	317	0.47	9	0	19	5
UK	3072	0.37	5	0	12	3
Japan	4016	0.51	5	1	10	3
Australia	2217	0.26	2	0	10	4
Hong Kong	1299	0.31	3	0	11	4
New Zealand	182	0.34	3	0	8	4
Singapore	711	0.32	3	0	9	3
All	21611	0.4	5.8	0.55	13	4.5

and form portfolios based on our media coverage measure. We exclude stocks with prices in the fifth price percentile at the end of each month in each country. We do this to exclude stocks with low prices, so-called penny stocks, to make sure that our results are not driven by small illiquid stocks. In the literature, there neither seems to be a clear definition of a penny stock, nor a consistent common methodology for price screening.[30] While some studies exclude stocks with prices lower than five dollars[31], others exclude stocks below one dollar or two dollars[32], and some others do not apply any price screening at all[33]. During our sample period, the percentage of all NYSE and NASDAQ stocks having prices below one (five) dollar in a given month ranges from 1% to 9% (10% to 37%). The proportion of low priced stocks is much larger during the

[30]E.g. Harris (1994) argues that penny stocks are defined by the SEC as stocks with prices below one dollar and that those have different minimum price variation limitations. Until 2001, the minimum price variation for stocks with prices lower than $1 was $1/16, since then it is $0.0001. This lessens bid-ask bounce and trading cost related issues for these stocks drastically. See e.g. He (2013).
[31]E.g. Amihud (2002).
[32]See e.g. Cooper, Gutierrez, and Hameed (2004), Kothari, Lewellen, and Warner (2006) and Lakonishok and Lee (2001).
[33]See e.g. Fama and French (2012) or Chordia and Shivakumar (2002).

burst of dot-com bubble in the beginning of the last decade and extremely magnified during the recent financial crisis 2007 to 2009. However, a large proportion of the stocks having low prices during these periods cannot be regarded as penny stocks.[34] They are simply low priced stocks, but with sufficient liquidity and no trade limitations are imposed on them. Excluding stocks below five dollars implies the omission of a large portion of the stock market, especially during turbulent times. We believe that adopting a five dollar price screening may introduce a strong bias in our sample of stocks over time, omitting relevant information for the present study.

Furthermore, we require stocks to be actively traded during the portfolio formation month and to have price and market capitalization data in order to be included in our sample. We exclude returns above 500% and below −95% per month to avoid unrealistically high/low returns, possibly caused by database errors, driving our results.

Table II. **Market State Measure - Summary Statistics**. The market state is considered to be good/bullish (bad/bearish) in a given month if the fraction of stocks with positive (negative) returns exceeds 50%. Equally weighted monthly market returns over the entire sample period and equally weighted monthly market returns and standard deviations during good, as well as during bad market state months are tabulated. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Countries	Average Fraction of Stocks w Positive Ret.	Fraction of Good State Months	Total Market Return	Equally Weighted Market Average Return and Volatility			
				Good States		**Bad States**	
				Mean	Std. Dev.	Mean	Std. Dev.
USA	0.52	0.57	0.0122**	0.0505***	0.035	-0.0395***	0.044
UK	0.41	0.26	0.0013	0.0554***	0.039	-0.0176***	0.041
Japan	0.47	0.45	0.0041	0.0491***	0.027	-0.0329***	0.033
Australia	0.44	0.38	0.0109*	0.0734***	0.041	-0.0275***	0.054
Hongkong	0.43	0.35	0.0153**	0.0973***	0.064	-0.0286***	0.062
New Zealand	0.48	0.54	0.0080***	0.0342***	0.021	-0.0222***	0.026
Singapore	0.44	0.40	0.0075	0.0736***	0.056	-0.0366***	0.052
Austria	0.47	0.41	0.0083**	0.0374***	0.028	-0.0122***	0.037
Belgium	0.50	0.55	0.0066**	0.0266***	0.020	-0.0182***	0.034
Denmark	0.48	0.50	0.0059	0.0414***	0.026	-0.0291***	0.039
Finland	0.49	0.51	0.0076*	0.0490***	0.039	-0.0354***	0.036
France	0.48	0.50	0.0083**	0.0436***	0.027	-0.0275***	0.038
Germany	0.43	0.28	0.0045	0.0556***	0.026	-0.0158***	0.041
Greece	0.39	0.30	-0.0099	0.0933***	0.074	-0.0549***	0.069
Italy	0.46	0.47	-0.0008	0.0448***	0.033	-0.0413***	0.043
Netherlands	0.49	0.50	0.0053	0.0452***	0.034	-0.0351***	0.046
Norway	0.47	0.46	0.0080	0.0593***	0.034	-0.0366***	0.053
Spain	0.48	0.48	0.0049	0.0458***	0.030	-0.0325***	0.036
Sweden	0.46	0.42	0.0046	0.0638***	0.044	-0.0381***	0.044
Switzerland	0.50	0.54	0.0044	0.0350***	0.023	-0.0319***	0.038

In Table II we present summary statistics for our market state measure. Column one displays

[34]E.g. Citigroup during 2009 traded well below $5.

the average fraction of stocks with positive monthly returns over our sample period for each country. Column two shows the percentage of good market state months over the entire sample period. For both measures, we observe quite some heterogeneity across countries. The U.S., Belgium and Switzerland for example have a relatively high fraction of good market state months (more than 50%), whereas in countries as the UK or Germany this fraction is below 30%. Column three contains the average market return over the entire sample period, columns four and five (six and seven) the average monthly market return and standard deviation during good (bad) market months. Table II demonstrates that our market state measure captures high (low) average market returns during good (bad) market states.

4 Results

We present our results in three sections. In the first Section 4.1, we focus on the U.S. and investigate whether the media effect that Fang and Peress (2009) found is still valid during our more recent sample period and using our media coverage measure. In Section 4.2, we present international evidence on the existence of no-media premiums. We examine whether the media effect that we find in the U.S. is an internationally observable phenomenon. Finally, we analyze the media effect conditional on the market state. The corresponding results across countries are presented in Section 4.3.

4.1 The Media Premium in the U.S.

The media effect we find in the U.S. (see Panel A of Table III) for the time period 1999 to 2012 is comparable, both in terms of magnitude and significance, to what Fang and Peress (2009) found for their 1993 to 2002 sample period. For a formation and holding period equal to one month, the average returns on stocks with no, low and high coverage are 1.36%, 1.20% and 0.92% per month compared to 1.35%, 1.11% and 0.96% in Fang and Peress (2009). The return differential between the portfolio of stocks with no- and the portfolio of stocks with high-media coverage is statistically significant and economically meaningful and amounts to 0.45% per month (compared to 0.39% per month in Fang and Peress (2009)). This return difference cannot be fully explained by commonly used risk factors. Although adding the factors absorbs about a third of the return differential - it decreases from 0.45% to 0.32% per month after controlling for market, size, book-to-market and momentum factors - the resulting CAPM-, Fama-French-, as well as Carhart-alphas remain statistically significant[35] and with about 3.84% per annum also economically important.

The first three columns of Panel A in Table III show that not only stocks with no-media coverage, but also stocks with low- and high-media coverage exhibit significantly positive alphas on average. Moreover, the alphas decrease monotonically as media coverage increases. These two observations indicate that that the observed media effect mainly comes from the portfolio consisting of stocks, which are not covered by mass media. As Fang and Peress (2009) point out, this suggests that the observed media effect is unlikely to be related to findings of e.g. Barber and Odean (2008) that individual investors tend to buy attention-grabbing stocks. If this was the cause of the findings, we would expect the media effect to be driven by negative subsequent returns on stocks with high-media coverage.

In a next step, we investigate the persistence of the no-media premium for longer portfolio formation and holding horizons. To do so, we form portfolios based on media coverage over 1 to 12 month periods (portfolio formation periods) and hold them for holding periods ranging from 1 to 12 months. Panel B in Table III depicts time-series means, CAPM-, Fama-French- and Carhart-alphas for the zero-investment strategy that goes long no-coverage stocks and short high-coverage stocks at the different portfolio formation and holding periods. The results illustrate that the media effect persists far beyond the one month formation and holding period horizon. The no-media premium becomes more stable and stronger as we increase the formation period and it remains highly statistically significant at all considered holding horizons.[36]

In Table IV[37] we investigate whether the media effect in the U.S. is stable when sorting with respect to various company characteristics and whether it is related to a lack of liquidity.[38]

[35]Two-sided p-values are 1.38%, 5.80% and 5.95%, respectively.

[36]The effects are considerably stronger, both in terms of magnitude and significance, than the corresponding long-term results in Fang and Peress (2009).

[37]The results in Table IV are for formation and holding periods of one month.

[38]We proxy the degree of liquidity of the stocks in our sample using four measures: Price, Amihud's illiquidity ratio, bid-ask spread and trading volume. Fang and Peress (2009) point out that the media effect could represent an arbitrage opportunity, which persists because impediments prevent rational investors from trading it. If this

Table III. Media Premiums in the U.S. Market. **Panel A** reports the profitability of equally weighted portfolios formed according to media coverage. At the end of each month t, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. No-High (Low-High) represents a zero-investment portfolio long stocks with No (Low) media coverage and short stocks with High media coverage. Time-series means plus alpha estimates from regressing the resulting monthly excess returns on the No, Low and High portfolios and returns on the long-short portfolios on widely accepted risk factors are presented. **Panel B** reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Panel A: Returns on Media Portfolios					
Regression Model	No	Low	High	No-High	Low-High
TS Mean	0.0136	0.0120	0.0092	0.0045**	0.0028**
CAPM Alpha	0.0108***	0.0089***	0.0060***	0.0048**	0.0029***
FF Alpha	0.0066***	0.0051***	0.0034**	0.0032*	0.0017*
Carhart Alpha	0.0068***	0.0052***	0.0036***	0.0032*	0.0016*

Panel B: Longer Formation and Holding Periods				
Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel B.1: Formation Period = 1 Month				
1 month	0.0045**	0.0048**	0.0032*	0.0032*
3 months	0.0047**	0.0051***	0.0036**	0.0035**
6 months	0.0043**	0.0046**	0.0032**	0.0032**
9 months	0.0043**	0.0046**	0.0032**	0.0032**
12 months	0.0041**	0.0044**	0.0030**	0.0030*
Panel B.2: Formation Period = 3 Months				
1 month	0.0051*	0.0057**	0.0053**	0.0052**
3 months	0.0044*	0.0050**	0.0045**	0.0044**
6 months	0.0041	0.0047*	0.0042*	0.0042*
9 months	0.0038	0.0043*	0.0040*	0.0039*
12 months	0.0035	0.0040*	0.0036*	0.0036*
Panel B.3: Formation Period = 6 Months				
1 month	0.0057*	0.0066***	0.0061***	0.0061***
3 months	0.0054*	0.0063**	0.0057**	0.0057**
6 months	0.0052*	0.0061**	0.0057**	0.0056**
9 months	0.0049*	0.0057**	0.0053**	0.0053**
12 months	0.0044	0.0052**	0.0047**	0.0046**
Panel B.4: Formation Period = 9 Months				
1 month	0.0074**	0.0080***	0.0078***	0.0078***
3 months	0.0064**	0.0070***	0.0067***	0.0067***
6 months	0.0057**	0.0063**	0.0061***	0.0061***
9 months	0.0054*	0.0060**	0.0057**	0.0056**
12 months	0.0051*	0.0056**	0.0052**	0.0052**
Panel B.5: Formation Period = 12 Months				
1 month	0.0071**	0.0086***	0.0083***	0.0083***
3 months	0.0059*	0.0073***	0.0070***	0.0069***
6 months	0.0055*	0.0069***	0.0065***	0.0064***
9 months	0.0050*	0.0063**	0.0059***	0.0058**
12 months	0.0048*	0.0060**	0.0056**	0.0055**

To do so, we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form our usual no-, low- and high-media coverage portfolios and calculate the subsequent returns on the media based long-short strategy. The resulting returns

is true, the media effect should be strongest among the most illiquid stocks.

Table IV. Conditional Media Premiums in the U.S. Market. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
		Panel 1: By MV		
1	-0.0017	-0.0011	-0.0007	-0.0011
2	-0.0044*	-0.0040*	-0.0049**	-0.0050***
3	0.0018	0.0020	0.0010	0.0008
		Panel 2: By MTBVyearly		
1	0.0026	0.0031	0.0036	0.0034
2	0.0008	0.0010	0.0002	0.0001
3	0.0027	0.0027	0.0011	0.0011
		Panel 3: By RETpastyear		
1	0.0018	0.0023	0.0005	0.0002
2	0.0027	0.0029	0.0009	0.0008
3	0.0101***	0.0103***	0.0094***	0.0095***
		Panel 4: By RETcurrentmonth		
1	0.0110***	0.0114***	0.0104***	0.0103***
2	0.0026	0.0029	0.0008	0.0008
3	-0.0007	-0.0004	-0.0020	-0.0021
		Panel 5: By Pavgpast		
1	0.0023	0.0030	0.0035	0.0031
2	-0.0012	-0.0007	-0.0020	-0.0022
3	0.0033*	0.0035**	0.0014	0.0013
		Panel 6: By BidAskSpread		
1	0.0036	0.0039*	0.0002	0.0000
2	0.0041*	0.0042*	0.0032	0.0031
3	0.0042	0.0045*	0.0048*	0.0046*
		Panel 7: By VAavgpastyear		
1	-0.0030	-0.0027	-0.0017	-0.0017
2	-0.0037**	-0.0036**	-0.0031**	-0.0031**
3	0.0013	0.0011	0.0017	0.0017
		Panel 8: By Amihud		
1	0.0029*	0.0030**	0.0024*	0.0024*
2	-0.0038*	-0.0036**	-0.0038**	-0.0037**
3	-0.0015	-0.0011	0.0002	0.0005

are evaluated against the risk factors.

In terms of magnitude, we find the media effect to be stronger among large companies (Panel 1), companies that have a low market-to-book value (Panel 2), and among high momentum-stocks (Panel 3). The results for our illiquidity measures (Panels 5 to 8) are inconclusive. The sorts by price and bid-ask spread indicate that the media effect is strongest among rather illiquid stocks, whereas sorts by trading volume and Amihud's illiquidity ratio suggest the opposite.

As in Fang and Peress (2009), Panel 4 of Table IV shows that the no-media premium is large and significant among stocks that have low current month returns and (insignificant) negative among stocks with high current month returns. This seems to be in line with continuation/reversal patterns among winner and loser stocks (*H3*) and raises the concern that our unconditional results could be rooted in these patterns (as formulated in *H4*). Yet, also among the set of stocks with low current month returns, we observe significant positive Carhart-alphas on the portfolio containing stocks with high media coverage and on the portfolio without media coverage.[39] Hence, losing stocks with concurrent news do not continue losing and there is also no evidence for a short-term reversal of losing stocks without news coverage. This is not consistent with the continuation/reversal patterns among loser stocks that form the basis of what *H3* predicts and thus provides evidence against our results being rooted in these effects.

Overall, the media effect in the U.S. is not particularly stable across subsamples of firm characteristics. For the entire cross-section of U.S. stocks on the other hand, it appears to be a stable phenomenon that is of an economically important magnitude and that exists across a wide range of alternative time horizons and that seems to be in line with *H2*.

4.2 International Media Premiums

In this chapter, we analyze international media effects across countries. In Section 4.2.1 we present unconditional results. We attempt to identify countries exhibiting a significant media effect. If the conclusion of Fang and Peress (2009) that the no-media premiums represent a compensation for holding stocks with low investor recognition is true, we should observe the effects found in the U.S. in different markets as well. In Section 4.2.2 we investigate whether our unconditional results are driven by the continuation/reversal patterns found in Chan (2003) and Tetlock (2010). In Section 4.2.3 we adopt a firm characteristics based conditional perspective in order to find out whether there are particular subgroups of stocks for which the media effect is pronounced and systematic across countries.

[39]See Panel 1 in Table IX in the Appendix.

4.2.1 Unconditional Media Premiums across Countries

Table V presents returns on portfolios sorted according to media coverage in the 20 countries in our sample over the entire sample period 1999 to 2012. The results are for a portfolio formation and holding period equal to one month. The first three columns of the table contain time-series means and factor alphas for the three portfolios with no-, low- and high-media coverage. Column four (five) contains the same information for the zero-investment strategy being long the no-coverage (low-coverage) and short the high-coverage stocks. We focus on the no-high coverage strategy throughout this paper. Results for portfolio formation and holding periods beyond one month are contained in Section A.2 in the Appendix.

Table V shows that for 14 countries the return differential between stocks with no- and stocks with high-media coverage is positive[40], ranging from statistically significant and economically meaningful 0.95% per month (about 11% p.a.) in Hongkong, to statistically insignificant and economically negligible 0.02% per month in Sweden. In addition to the U.S., the return differentials are significantly positive after controlling for risk factors in Hongkong, Germany, France, Switzerland, Spain, the Netherlands, Belgium and Austria. For the remaining six countries, namely New Zealand, Singapore, the UK, Italy, Denmark and Greece, we find a negative media effect. The UK (with −0.47% per month) is the only country with a significant negative effect.

Panels 7 to 20 in Table V contain unconditional results for the 14 European countries in our sample. In France, Switzerland, Spain, the Netherlands, Belgium and Austria (and to some degree Germany) the return differentials between stocks without media coverage and those with high media coverage in a given month are positive, economically meaningful and statistically highly significant[41] after controlling for all risk factors. The first three columns of the respective Panels in Table V reveal that mainly the long legs of the strategy (the no-coverage stocks) exhibit significantly positive alphas. This suggests that, as in the U.S., the observed media effect for these European countries primarily stems from the portfolios containing stocks that are not covered by mass media.

[40] For the USA, Australia, Hongkong, Japan, Germany, France, Switzerland, Spain, Sweden, Netherlands, Belgium, Norway, Finland and Austria.
[41] Two-sided p-values for the alphas are all below 5%.

Table V. Media Premiums Across Countries. This table reports the profitability of equally weighted portfolios formed according to media coverage. At the end of each month t, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. No-High (Low-High) represents a zero-investment portfolio long stocks with No (Low) media coverage and short stocks with High media coverage. Time-series means plus alpha estimates from regressing the resulting monthly excess returns on the No, Low and High portfolios and returns on the long-short portfolios on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Regression Model	No	Low	High	No-High	Low-High
Panel 1: USA					
TS Mean	0.0136	0.0120	0.0092	0.0045**	0.0028**
CAPM Alpha	0.0108***	0.0089***	0.0060***	0.0048**	0.0029***
FF Alpha	0.0066***	0.0051***	0.0034**	0.0032*	0.0017*
Carhart Alpha	0.0068***	0.0052***	0.0036***	0.0032*	0.0016*
Panel 2: Australia					
TS Mean	0.0180	0.0153	0.0125	0.0055	0.0028
CAPM Alpha	0.0156	0.0128	0.0101	0.0054	0.0027
FF Alpha	0.0199**	0.0186**	0.0162**	0.0037	0.0024
Carhart Alpha	0.0295***	0.0281***	0.0243***	0.0052*	0.0038
Panel 3: Hongkong					
TS Mean	0.0172	0.0115	0.0077	0.0095**	0.0038
CAPM Alpha	0.0080	0.0013	-0.0026	0.0107**	0.0040
FF Alpha	0.0018	-0.0058***	-0.0069***	0.0086***	0.0011
Carhart Alpha	0.0017	-0.0051**	-0.0054**	0.0071***	0.0003
Panel 4: Japan					
TS Mean	0.0065	0.0058	0.0044	0.0021	0.0014
CAPM Alpha	0.0069**	0.0063**	0.0051***	0.0018	0.0012
FF Alpha	0.0024**	0.0020**	0.0017*	0.0007	0.0003
Carhart Alpha	0.0023**	0.0019**	0.0016**	0.0007	0.0003
Panel 5: NewZealand					
TS Mean	0.0127	0.0170	0.0156	-0.0030	0.0013
CAPM Alpha	0.0050	0.0088**	0.0077	-0.0027	0.0011
FF Alpha	0.0056	0.0098**	0.0090	-0.0034	0.0008
Carhart Alpha	0.0064*	0.0096**	0.0093	-0.0029	0.0003
Panel 6: Singapore					
TS Mean	0.0102	0.0086	0.0123	-0.0021	-0.0037*
CAPM Alpha	0.0012	-0.0003	0.0037**	-0.0024	-0.0040*
FF Alpha	-0.0002	-0.0017	0.0015	-0.0017	-0.0031
Carhart Alpha	0.0004	-0.0016	0.0018	-0.0013	-0.0034
Panel 7: UK					
TS Mean	0.0001	0.0033	0.0047	-0.0047**	-0.0014
CAPM Alpha	-0.0032	-0.0001	0.0012	-0.0044**	-0.0013
FF Alpha	0.0042	0.0075	0.0076	-0.0034*	-0.0001
Carhart Alpha	0.0102*	0.0134**	0.0129***	-0.0028	0.0004
Panel 8: Germany					
TS Mean	0.0093	0.0013	0.0020	0.0073**	-0.0007
CAPM Alpha	0.0082	0.0003	0.0010	0.0072***	-0.0007
FF Alpha	0.0135*	0.0077	0.0082	0.0053*	-0.0005
Carhart Alpha	0.0209***	0.0177***	0.0178***	0.0031	-0.0001
Panel 9: France					
TS Mean	0.0131	0.0057	0.0058	0.0074**	-0.0001
CAPM Alpha	0.0124	0.0053	0.0057	0.0067***	-0.0004
FF Alpha	0.0175***	0.0110*	0.0119**	0.0056***	-0.0009
Carhart Alpha	0.0191***	0.0129**	0.0136***	0.0056***	-0.0007
Panel 10: Switzerland					
TS Mean	0.0093	0.0092	0.0042	0.0051*	0.0049**
CAPM Alpha	0.0108	0.0109	0.0062	0.0046**	0.0047**
FF Alpha	0.0121**	0.0127**	0.0077	0.0044**	0.0050***
Carhart Alpha	0.0150***	0.0160***	0.0113**	0.0038**	0.0047**

Table V. Media Premiums Across Countries - Continued

Regression Model	No	Low	High	No-High	Low-High
			Panel 11: Spain		
TS Mean	0.0087	0.0083	0.0035	0.0052	0.0048*
CAPM Alpha	0.0048	0.0034	-0.0015	0.0063**	0.0049**
FF Alpha	0.0044	0.0038	-0.0020	0.0063***	0.0057***
Carhart Alpha	0.0061**	0.0063***	-0.0001	0.0062**	0.0064***
			Panel 12: Sweden		
TS Mean	0.0070	0.0050	0.0068	0.0002	-0.0017
CAPM Alpha	0.0055	0.0034	0.0050	0.0005	-0.0016
FF Alpha	0.0098	0.0079	0.0073	0.0024	0.0005
Carhart Alpha	0.0142*	0.0113	0.0115	0.0028	-0.0002
			Panel 13: Netherlands		
TS Mean	0.0106	0.0032	0.0039	0.0067**	-0.0006
CAPM Alpha	0.0068**	-0.0005	-0.0001	0.0069***	-0.0004
FF Alpha	0.0061**	-0.0012	0.0002	0.0060**	-0.0014
Carhart Alpha	0.0061**	-0.0013	0.0002	0.0059**	-0.0014
			Panel 14: Belgium		
TS Mean	0.0131	0.0074	0.0042	0.0089***	0.0032
CAPM Alpha	0.0097***	0.0034*	-0.0002	0.0100***	0.0036*
FF Alpha	0.0070***	0.0004	-0.0028	0.0098***	0.0032
Carhart Alpha	0.0065***	0.0006	-0.0021	0.0086***	0.0027
			Panel 15: Norway		
TS Mean	0.0112	0.0101	0.0068	0.0043	0.0033
CAPM Alpha	0.0009	-0.0011	-0.0058*	0.0067*	0.0047
FF Alpha	0.0003	-0.0017	-0.0058*	0.0061*	0.0042
Carhart Alpha	0.0020	0.0011	-0.0039	0.0059	0.0050
			Panel 16: Italy		
TS Mean	0.0004	0.0011	0.0010	-0.0007	0.0001
CAPM Alpha	0.0010	0.0021	0.0026	-0.0015	-0.0004
FF Alpha	0.0015	0.0023	0.0018	-0.0003	0.0004
Carhart Alpha	0.0058	0.0060	0.0054	0.0004	0.0006
			Panel 17: Finland		
TS Mean	0.0104	0.0074	0.0052	0.0052	0.0022
CAPM Alpha	0.0063*	0.0030	0.0004	0.0059**	0.0026
FF Alpha	0.0056**	0.0015	-0.0000	0.0056*	0.0015
Carhart Alpha	0.0046*	0.0017	0.0010	0.0036	0.0008
			Panel 18: Austria		
TS Mean	0.0124	0.0090	0.0080	0.0044	0.0011
CAPM Alpha	0.0063**	0.0010	-0.0016	0.0079**	0.0026
FF Alpha	0.0059**	0.0007	-0.0017	0.0077**	0.0024
Carhart Alpha	0.0064**	0.0014	-0.0010	0.0074**	0.0024
			Panel 19: Denmark		
TS Mean	0.0084	0.0058	0.0119	-0.0035	-0.0062
CAPM Alpha	0.0046	0.0018	0.0072*	-0.0027	-0.0055
FF Alpha	0.0007	-0.0011	0.0062	-0.0055	-0.0074**
Carhart Alpha	-0.0000	-0.0008	0.0070	-0.0071*	-0.0078**
			Panel 20: Greece		
TS Mean	-0.0062	-0.0081	-0.0040	-0.0022	-0.0041
CAPM Alpha	-0.0108*	-0.0135**	-0.0097*	-0.0012	-0.0039
FF Alpha	-0.0153**	-0.0186***	-0.0153***	-0.0000	-0.0033
Carhart Alpha	-0.0110	-0.0148**	-0.0116*	0.0006	-0.0032

With the exception of France[42] and Spain, the media effect extends to formation and holding periods beyond the one month horizon (see Tables I to VIII in Section A.2 in the Appendix), though by far not as consistently as in the U.S. Still, the fact that the media effect mainly comes from the long leg of our strategy, combined with the observation that the effect is not short-lived, provides a first indication for that our results are unlikely to be related to the

[42]In France we observe the media effect only at the 1-month holding horizon, but at all portfolio formation horizons.

continuation/reversal patterns modeled in Tetlock (2010) and found in Chan (2003).

The media effect we find in the largest European stock market, the UK, is negative. As can be seen in Table VII in Section A.2 in the Appendix, we observe a highly significant negative media effect at most portfolio formation and holding periods that we consider, implying that the negative media effect we find for the cross-section of UK stocks is not only a short-term phenomenon but robust across alternative horizons. Panel 7 of Table V shows that, opposed to the aforementioned countries, the returns on our three media portfolios monotonically increase with the degree of media coverage. Stocks with a high media coverage outperform those neglected by mass media, implying that the negative media effect we observe in the UK mainly comes from the high returns on the short leg of our strategy.

Panels 2 to 6 of Table V show the results for Japan and the APAC countries in our sample. The only country with a significant media effect in this group is Hongkong, with a positive time-series mean of 0.95% per month and an economically meaningful and highly significant alpha of 0.71% per month after controlling for market, size, book-to-market and momentum factors. Examining the alphas of the individual portfolios indicates that - in contrast to the European countries with a positive effect - the effect seems to mainly come from shorting stocks with high media coverage, which yield negative returns on average.[43] As Table VIII in the Appendix shows, the significant positive media effect in Hongkong persists at all holding and formation periods that we consider.

Overall, the results presented in this section suggest that there are considerable differences as to the magnitude, direction and persistence of the media effect across countries. We do not find consistent evidence for the existence of premiums that compensate investors for holding stocks with low investor recognition in all countries. We have a significant positive effect in seven countries and a significant negative effect in the UK. Hence, the media effect patterns verified in the U.S. do not seem to be a consistent and wide-spread property of the cross-section of stock returns in developed markets. Nevertheless, as we will show in the two next sections, there are subgroups of stocks among which the media effect seems to be a stable property that can be

[43]This is also true at longer holding and formation horizons and is hence consistent with the negative return drift of “news losers” found in Chan (2003).

observed in most developed markets.

4.2.2 Media Premiums and Continuation/Reversal Patterns

Results on the media premiums within portfolios of stocks sorted with respect to current month return terciles are displayed in Table VI and provide a consistent pattern: All countries in our sample, with the exception of the UK, provide an economically large positive no-media premium among the low current month return tercile stocks. The effect is statistically significant in 16 out of 20 countries.[44] On the other hand, stocks with high current month returns display a negative no-media premium in 18 out of 20 countries[45], but only eight[46] countries' stock markets result in significantly negative no-media premiums after controlling for risk factors. These patterns seem to be in line with the implications of the asymmetric information model in Tetlock (2010) and the findings of Chan (2003) outlined in Section 2.1 (H3). A look at Tables IX and X in the Appendix however reveals that this is actually the case only for a few countries. Tables IX and X in the Appendix contain details on current month loser and current month winner portfolios in all countries, for holding periods from 1 to 12 months. Carhart-alphas on the portfolios with no- and high-media coverage are displayed in columns two and three, the no-high Carhart-alphas are in the last column.

According to Table IX, only Hongkong, Singapore, the Netherlands, Belgium, Norway, Finland and Austria actually display return patterns among loser stocks that are broadly consistent with what reversal/continuation patterns imply.[47] Nevertheless, this raises the concern that the significant positive unconditional no-media premiums we find in Hongkong, the Netherlands, Belgium and Austria could in fact be driven by the current month losers' media effect, as formulated in *H4*.

[44]Not significant positive in the UK, Spain, Denmark and Greece.
[45]Hongkong and Spain are the exceptions with a positive effect.
[46]Australia, Japan, New Zealand, Singapore, Spain, Sweden, Finland and Denmark.
[47]Positive returns on no-coverage stocks (resulting from a short-term reversal) and negative returns on high-coverage stocks (resulting from a negative continuation/drift).

Table VI. Media Premiums Conditional on Current Month Returns. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to current month returns. At the end of each month t we first sort all stocks into terciles according to their returns during month t. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage	No-High		
RET current month	Low	Med	High
Panel 1: USA			
TS Mean	0.0110***	0.0026	-0.0007
CAPM Alpha	0.0114***	0.0029	-0.0004
FF Alpha	0.0104***	0.0008	-0.0020
CAR Alpha	0.0103***	0.0008	-0.0021
Panel 2: Australia			
TS Mean	0.0290***	0.0005	-0.0090**
CAPM Alpha	0.0288***	0.0005	-0.0090**
FF Alpha	0.0271***	-0.0010	-0.0109***
CAR Alpha	0.0280***	0.0001	-0.0091***
Panel 3: Hongkong			
TS Mean	0.0165***	0.0039	0.0081
CAPM Alpha	0.0176***	0.0051	0.0089
FF Alpha	0.0155***	0.0036	0.0057
CAR Alpha	0.0142***	0.0023	0.0034
Panel 4: Japan			
TS Mean	0.0070***	0.0015	-0.0034*
CAPM Alpha	0.0067***	0.0012	-0.0036*
FF Alpha	0.0050***	0.0008	-0.0041**
CAR Alpha	0.0050***	0.0009	-0.0041**
Panel 5: NewZealand			
TS Mean	0.0143**	-0.0119	-0.0133***
CAPM Alpha	0.0141**	-0.0114	-0.0129***
FF Alpha	0.0175***	-0.0139	-0.0159***
CAR Alpha	0.0201***	-0.0130	-0.0156***
Panel 6: Singapore			
TS Mean	0.0102***	-0.0017	-0.0148***
CAPM Alpha	0.0095**	-0.0014	-0.0149***
FF Alpha	0.0114***	-0.0011	-0.0162***
CAR Alpha	0.0120***	0.0001	-0.0163***
Panel 7: UK			
TS Mean	-0.0005	-0.0082***	-0.0030
CAPM Alpha	-0.0002	-0.0079***	-0.0028
FF Alpha	0.0016	-0.0068***	-0.0029
CAR Alpha	0.0022	-0.0062***	-0.0021
Panel 8: Germany			
TS Mean	0.0231***	0.0009	-0.0023
CAPM Alpha	0.0231***	0.0008	-0.0024
FF Alpha	0.0218***	-0.0009	-0.0040
CAR Alpha	0.0192***	-0.0034	-0.0046
Panel 9: France			
TS Mean	0.0193***	0.0039	-0.0010
CAPM Alpha	0.0187***	0.0033*	-0.0015
FF Alpha	0.0178***	0.0019	-0.0024
CAR Alpha	0.0176***	0.0024	-0.0023
Panel 10: Switzerland			
TS Mean	0.0082**	0.0020	-0.0010
CAPM Alpha	0.0078**	0.0017	-0.0014
FF Alpha	0.0077**	0.0015	-0.0019
CAR Alpha	0.0070**	0.0010	-0.0024

Table VI. Media Premiums Conditional on Current Month Returns - Continued

Media Coverage	No-High		
RET current month	Low	Med	High
Panel 11: Spain			
TS Mean	0.0048	0.0007	0.0072*
CAPM Alpha	0.0049	0.0020	0.0080**
FF Alpha	0.0051	0.0024	0.0075**
CAR Alpha	0.0040	0.0032	0.0073**
Panel 12: Sweden			
TS Mean	0.0109**	0.0002	-0.0111**
CAPM Alpha	0.0112***	0.0005	-0.0108**
FF Alpha	0.0127***	0.0016	-0.0091**
CAR Alpha	0.0142***	0.0016	-0.0085*
Panel 13: Netherlands			
TS Mean	0.0122**	0.0116***	-0.0024
CAPM Alpha	0.0118**	0.0127***	-0.0015
FF Alpha	0.0110**	0.0124***	-0.0021
CAR Alpha	0.0108**	0.0124***	-0.0021
Panel 14: Belgium			
TS Mean	0.0205***	0.0068**	-0.0039
CAPM Alpha	0.0216***	0.0075**	-0.0029
FF Alpha	0.0213***	0.0057*	-0.0021
CAR Alpha	0.0192***	0.0061*	-0.0033
Panel 15: Norway			
TS Mean	0.0221***	-0.0028	-0.0080*
CAPM Alpha	0.0246**	0.0002	-0.0062
FF Alpha	0.0232**	-0.0002	-0.0066
CAR Alpha	0.0205**	0.0010	-0.0075*
Panel 16: Italy			
TS Mean	0.0034	-0.0018	-0.0045
CAPM Alpha	0.0028	-0.0024	-0.0055
FF Alpha	0.0055*	-0.0017	-0.0052
CAR Alpha	0.0062*	-0.0015	-0.0046
Panel 17: Finland			
TS Mean	0.0157***	0.0069*	-0.0087*
CAPM Alpha	0.0163***	0.0076**	-0.0084**
FF Alpha	0.0186***	0.0073**	-0.0092**
CAR Alpha	0.0159***	0.0064*	-0.0123***
Panel 18: Austria			
TS Mean	0.0235***	0.0003	-0.0058
CAPM Alpha	0.0277***	0.0030	-0.0048
FF Alpha	0.0277***	0.0035	-0.0055
CAR Alpha	0.0270***	0.0035	-0.0056
Panel 19: Denmark			
TS Mean	0.0058	-0.0038	-0.0154***
CAPM Alpha	0.0066	-0.0031	-0.0149***
FF Alpha	0.0051	-0.0025	-0.0163***
CAR Alpha	0.0027	-0.0042	-0.0167***
Panel 20: Greece			
TS Mean	0.0092	-0.0030	-0.0064
CAPM Alpha	0.0103	-0.0024	-0.0056
FF Alpha	0.0127*	-0.0028	-0.0056
CAR Alpha	0.0106	-0.0007	-0.0042

From Section 4.2.1 we know that the unconditional media effect in Hongkong is positive and highly significant at all considered portfolio holding and formation periods and driven by the negative returns on high coverage stocks: The Carhart-alpha on the high-coverage portfolio is significantly negative and large, while the positive Carhart-alpha on the no-coverage portfolio is not significantly different from zero. Combined with the fact that the Carhart-alpha on the high-coverage portfolio in the low current month return tercile (Panel 3 of Table IX in

Appendix) is significantly negative at all horizons, this indicates that it is possible that the positive unconditional media effect in Hongkong is in fact driven by the negative drift of "news-losers" in the sense of *H4*.

In the Netherlands and Austria, the significant positive unconditional media effect reported in Section 4.2.1 is persistent as well, and clearly driven by the positive returns on no-coverage stocks: The Carhart-alpha on the no-coverage portfolio is large and significantly positive in both countries, while the Carhart-alpha on the high-coverage portfolio is very small and positive in the Netherlands and slightly negative in Austria (in both cases not significantly different from zero). Hence, the positive unconditional media effect is not likely to come from the negative drift on "news losers".[48] It is as well unlikely that the positive unconditional media effect stems from a positive (short-term) reversal of "no-news losers": In the Netherlands, the alphas on the no-coverage portfolio in the low current month return tercile are not statistically different from zero at all considered horizons (see Table IX, Appendix), while the unconditional media effect is significant for holding horizons up to three months. In Austria the unconditional media effect is significant positive at all holding and formation horizons, while the reversal of "no-news losers" is only short-lived.

The significant positive unconditional media effect in Belgium is as well driven by the large positive returns on no-coverage stocks: The Carhart-alpha on the no-coverage portfolio is large and significantly positive, the Carhart-alpha on the high-coverage portfolio is negative (but not significantly different from zero). The latter observation implies that, as above, the positive unconditional media effect cannot be explained by the negative drift on "news losers". According to Panel 14 of Table IX, the Carhart-alphas on the no-media portfolio in the low current month return tercile are significantly positive in the short-run. As the unconditional media effect in Belgium is likewise just detectable in the short-run and mainly comes from the large positive returns on no-coverage stocks, this suggests that the positive unconditional media effect in Belgium may stem from the positive (short-term) reversal of "no-news losers".

From the eight countries seemingly in line with reversal/continuation effects among winners,

[48] Besides, the alphas on the high-coverage portfolio in the low current month return tercile are not statistically different from zero in the Netherlands at all considered horizons (see Table IX in Appendix).

only Japan, New Zealand, Singapore, Finland and Denmark actually display return patterns among winner stocks that are broadly consistent with reversal/continuation patterns.[49] Hence, it is possible that the reversal/continuation effects among winners are the reason for why we do not find significant positive unconditional no-media premiums in these countries.

Singapore and Finland are the only countries exhibiting return patterns that are consistent with continuation/reversal among winners, as well as among losers (see Panels 6 and 17 in Tables IX and X, respectively). Whereas in Finland the positive media effect among losers is stronger in absolute terms than the negative media effect among winners, the opposite applies to Singapore. Hence, if the stocks contained in the unconditional no-coverage portfolios correspond to no-news stocks (losers and winners) and those in the unconditional high-coverage portfolio correspond to news stocks (losers and winners), we would expect to find an unconditional media effect that is weakly positive in Finland and weakly negative in Singapore. And this is what we actually find in Section 4.2.1.[50]

In Japan, New Zealand and Denmark we only find return patterns consistent with continuation/reversal among current month winners, resulting in a negative media effect among current month winners (see Table X in Appendix). The could partly explain why we do not find significant positive no-media premiums in these countries.

Overall, although we observe significantly positive no-media premiums for current month losers across most countries, the significant positive unconditional no-media premiums that we find do not seem to be caused by return continuation/reversal effects. Only in Hongkong, and to a smaller degree in Belgium, the significant positive return differential between no- and high coverage stocks could in fact be rooted in continuation/reversal patterns as documented in Chan (2003) and modeled in Tetlock (2010).

---

[49] Negative returns on no-coverage stocks (resulting from a short-term reversal) and positive returns on high-coverage stocks (resulting from a positive continuation/drift).

[50] In Finland we have an insignificant positive unconditional media effect, that is driven by the significantly positive Carhart-alpha on the no-coverage portfolio, while the Carhart-alpha on the high-coverage portfolio is not significantly different from zero. In Singapore we see an insignificant negative unconditional effect. Carhart-alphas on no- and high-coverage portfolios are positive though not significantly different from zero, but the alpha on high-coverage portfolio is of a larger magnitude.

4.2.3 Media Premiums Conditional on Firm Characteristics

Tables presenting the double-sort results can be found in Section A.4 in the Appendix. They contain time-series means and risk-adjusted returns (alphas) on the no-high media coverage zero-investment portfolios for terciles of stocks, formed using the respective firm characteristics.

Results for the portfolios of stocks sorted with respect to market capitalization are presented in Table XI in the Appendix. They show that most stock markets provide a positive no-media premium among small cap stocks. The only exceptions are the U.S. and Denmark with insignificant negative premiums. New Zealand, Singapore, the UK, Germany, France, the Netherlands, Austria and Greece provide a statistically significant and large positive no-media premium among small caps after controlling for all risk factors. Interestingly, even for countries yielding a negative no-media premium in the entire cross-section (the UK, Italy, Greece, Singapore and New Zealand) we find a positive - for the UK, Greece and New Zealand yet statistically highly significant - no-media premium among the stocks in the lowest size tercile. Among large cap stocks on the other hand there is no significant positive media effect in any country.

Looking at our sorts with respect to measures that proxy for illiquidity (Tables XII to XV in the Appendix), the most consistent results are found among stocks with high bid-ask spreads. The portfolios consisting of stocks located in the highest bid-ask spread tercile exhibit a positive no-media premium in all countries in our sample. In the U.S., Hong Kong, Japan, New Zealand, the UK, Germany, France, Switzerland, Spain, Belgium, Norway and Austria the effect is statistically highly significant and of a large magnitude. Taken as a whole across all our illiquidity proxies, all countries but Singapore, Italy, Finland, Denmark and Greece display a significant positive media effect in at least one of the most illiquid terciles. Finland, Australia, Hongkong, Japan, Singapore, Germany and Austria display significant negative media effects among the most liquid stocks.

High past year return stocks, for most stock markets (16 out of 20) yield a positive no-media premium.[51] In the U.S., Hong Kong, Japan, New Zealand, the UK, France, Switzerland, Spain, the Netherlands, Belgium, Austria the effect is highly significant. The returns on the no-, low-

[51]The negative effect in the remaining four countries is insignificant.

and high-media coverage portfolios are monotonically decreasing as the coverage increases and the long-short return differential is generally driven by the long leg containing the no-media coverage stocks. Hence, high momentum stocks with high mass media coverage in a given month underperform those without media coverage. For past year losers, the effect is also predominantly positive (in 17 out of the 20 countries), but only in seven countries significantly so. See Table XVI in the Appendix.

Among the countries where we have significant positive unconditional no-media premiums (Hongkong, France, Switzerland, Spain, the Netherlands, Belgium and Austria), the media effect is in general positive and stable across firm characteristic terciles. The effect is always strongest among small companies and by trend more pronounced among past year winner stocks and more illiquid stocks. Nevertheless, all but Austria also display significant positive no-media premiums among more liquid stocks with a low or medium bid-ask spread. Moreover, we find significant positive no-media premiums for all of these countries (but Hongkong) among stocks in the highest price tercile. Thus, the positive unconditional media effect we find in these countries is not only prevalent among the most illiquid stocks.

The negative unconditional media effect in the UK is not stable when analyzed across firm characteristics. Although the effect remains negative in most double-sort terciles, it switches sign and becomes positive - consistent with what we observe in the other countries - among small stocks, past winner stocks and among the most illiquid stocks.

Overall, examining the media effect conditional on firm characteristics, we observe a considerable tendency in most stock markets towards smaller and more illiquid stocks providing a significant positive no-media premium. Independently on whether the unconditional media effect in a country is positive or negative, for these subgroups the effect consistently points into the same direction in the vast majority of countries. Hence, the role of mass media seems to be more important for these subsets of stocks, which arguably are characterized by rather poor information dissemination.

4.3 Market-States and Media Premiums

We introduce a simple measure to determine whether the market states are good or bad and analyze whether there are systematic differences in the media effect when we condition on this measure. We consider the market state in a given month to be good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%.[52]

Table VII provides evidence, indicating a notable degree of asymmetry in the media effect. The first two columns contain the average market states over our sample period and the fraction of months with good market states for all countries in our sample. The U.S. is the only country in which the market state is good on average. In the last five columns of Table VII we summarize the returns of our media coverage based long-short strategy, conditional on market states. As can be seen in column three, across all countries, stocks with high-media coverage have significantly higher concurrent returns than stocks not covered by mass media during good market months. During bad market state months, the picture is not so clear-cut. Column five shows that in half of the countries stocks without coverage during bad market state months outperform those with high coverage.

More importantly, in all countries but Greece and Denmark, portfolios containing stocks that are not covered by mass media during good market state months subsequently clearly outperform portfolios containing stocks that are highly covered during good market months. This can be seen in column four of Table VII. There is a positive, mostly economically large no-media premium in 18 out of the 20 markets in our sample, when we condition on the market states being good.[53]

On the other hand, only one country (Belgium) displays a significant positive media effect when we condition on bad market states (column six of Table VII). In the UK, New Zealand, Singapore and Sweden we find significant negative no-media premiums; stocks highly covered by mass media during bad market state months subsequently outperform those not covered by

[52]Results for using positive/negative equally-weighted market returns to approximate good/bad market states are contained in Table XXIX in the Internet Appendix. The results are qualitatively similar.

[53]Significant positive in 12 countries: Japan, Australia, New Zealand, Germany, Sweden plus in the countries that exhibit a significant positive unconditional no-media effect (the U.S., Hongkong, Austria, Belgium, France, the Netherlands, Spain, Switzerland).

Table VII. **Market States and Media Premiums - Summary Statistics**. At the end of each month t, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. We form a zero-investment portfolio long stocks with No media coverage and short stocks with High media coverage. The portfolio is held during month $t+1$ and rebalanced monthly. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. The resulting average month t (current returns) and month $t+1$ zero-investment returns (subsequent returns) conditional on good/bad market states are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Countries	Average Fraction of Stocks w Positive Ret.	Fraction of Good State Months	Average Return No-High Coverage Zero-Investment Portfolio Good State Months Current	Subsequent	Bad State Months Current	Subsequent	Return Difference Good vs. Bad States Subsequent
USA	0.52	0.57	-0.0173***	0.0100***	0.0099***	-0.0030	0.0130***
UK	0.41	0.26	-0.0342***	0.0074	-0.0227***	-0.0090***	0.0163***
Japan	0.47	0.45	-0.0201***	0.0053**	-0.0044**	-0.0005	0.0058**
Australia	0.44	0.38	-0.0172**	0.0242***	-0.0242***	-0.0057	0.0299***
Hongkong	0.43	0.35	-0.0182**	0.0313***	-0.0168***	-0.0021	0.0334***
New Zealand	0.48	0.54	-0.0225***	0.0064**	-0.0034	-0.0138**	0.0202***
Singapore	0.44	0.40	-0.0139***	0.0042	-0.0211***	-0.0064*	0.0106**
Austria	0.47	0.41	-0.0252***	0.0040	0.0217***	0.0048	-0.0007
Belgium	0.50	0.55	-0.0222***	0.0079**	0.0203***	0.0102*	-0.0023
Denmark	0.48	0.50	-0.0246***	-0.0025	0.0030	-0.0045	0.0020
Finland	0.49	0.51	-0.0146***	0.0049	0.0109***	0.0056	-0.0007
France	0.48	0.50	-0.0196***	0.0145***	0.0158***	0.0004	0.0141***
Germany	0.43	0.28	-0.0310***	0.0139***	0.0065	0.0046	0.0093
Greece	0.39	0.30	-0.0054	-0.0033	-0.0116*	-0.0017	-0.0016
Italy	0.46	0.47	-0.0278***	0.0021	-0.0011	-0.0031	0.0052
Netherlands	0.49	0.50	-0.0266***	0.0100***	0.0147***	0.0032	0.0068
Norway	0.47	0.46	-0.0429***	0.0067	0.0046	0.0022	0.0045
Spain	0.48	0.48	-0.0301***	0.0106***	0.0107***	0.0001	0.0106*
Sweden	0.46	0.42	-0.0382***	0.0086*	-0.0091**	-0.0058*	0.0144**
Switzerland	0.50	0.54	-0.0230***	0.0090**	0.0204***	0.0003	0.0086

media during bad market months. In the remaining countries, the return differential between no- and high-media coverage stocks is not statistically different from zero, often has a negative prefix, and in case it is positive, is of a much smaller magnitude than after good market months.[54] The last column of Table VII contains the differences in average returns of the No-High media coverage zero-investment strategy between good and bad market state months. The differences are statistically significant in ten countries.

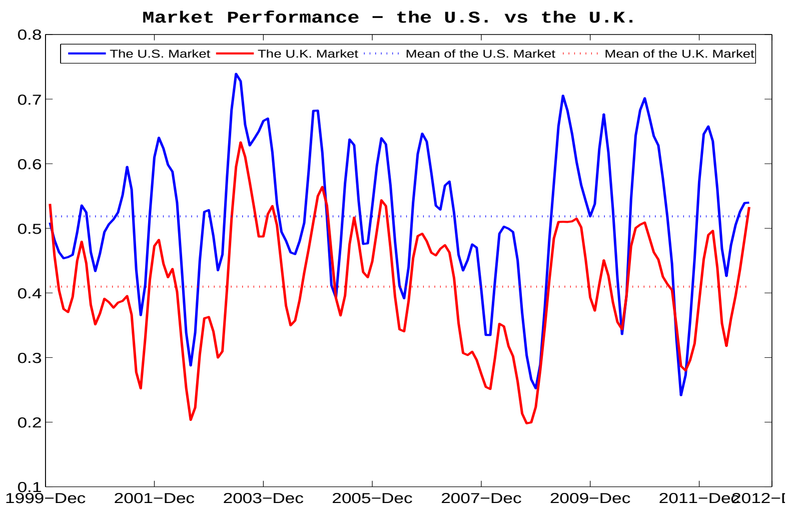
The observations so far provide evidence in favor of *H5*. In most countries - especially in those

[54] Only exceptions to this are Austria and Finland.

with large stock markets - the media effect is large and positive in good market states and not significant or even negative in bad market states. No country displays effects consistent with what continuation/reversal explanations (*H6*) would suggest. The results in Japan, Australia, Germany, plus in the countries that exhibit a significant positive unconditional media effect[55] are entirely consistent with *H5*: A significant positive no-media premium when we condition on positive market states and an insignificant premium conditional on bad market states. Thus, the no-high media coverage strategy is not consistently profitable independent of the market states - similar to momentum premiums, as pointed out by Chordia and Shivakumar (2002) or Cooper, Gutierrez, and Hameed (2004).

At the end it is the asymmetry in the direction and absolute magnitude of the media effect over good/bad market state months, combined with the fraction of good/bad market months, that determines whether we find a positive or negative unconditional no-media premium in the cross-section of stocks in the respective markets.

Figure 1. Cross-sectional fraction of stocks with positive returns in each month in the U.S. and the UK over time. The presented values are smoothed with a moving average of lag 5.



As Table VII indicates, the positive media effect we find in the cross-section of all U.S. stocks for example, seems to be a consequence of the relatively few bad market months during the sample period and the asymmetry, both in terms of sign and magnitude, of the media effect between good/bad market months. A comparison to the UK makes this mechanism clear-cut.

[55]Austria and Belgium are the exceptions.

The U.S. has the highest proportion of good states over the whole sample period, with 57% of the months being good states, whereas the UK has the lowest proportion of good market state months (only 26%). Figure 1 plots the (smoothed) market state measure for the U.S. and the UK over time, together with the respective market state means. We observe that the two market state lines are highly correlated. Nevertheless, the market states are bad on average in the UK and good on average in the U.S., and the U.S. stock market outperforms the UK stock market almost all the time. Hence, whereas in the U.S. good market state months dominate bad market state months (both, in terms of count and absolute magnitude of the effect), we observe the opposite in the UK. There are more negative market state months, and the magnitude of the negative effect in bad market state months clearly dominates the positive effect in good market state months. As a consequence, we observe a negative unconditional no-media premium in the cross-section of all UK stocks when we look at our entire sample period.

Table VIII presents the return premiums that result when we apply our market state measure as a (out-of-sample) signal on the original long-short strategy. Instead of always being long no-coverage stocks and and short high coverage stocks, we reverse the long-short portfolio by taking a long position on high media coverage stocks and a short position on no-media coverage stocks when the market state is bad. Of course, this only makes the results stronger in markets where the media effects' return prefix changes to negative following bad market state months.[56]

As Table VIII reveals, such a strategy consistently yields highly significant and large positive portfolio returns. In the U.S. for example, the Carhart-alpha more than doubles compared to the original long-short; 0.70% compared to 0.32% per month. In the U.S., Japan and all APAC countries (Hongkong, Singapore, Australia, New Zealand), as well as in the UK, Germany, France, Switzerland, Spain and Sweden we observe significantly positive return premiums of large magnitudes after controlling for all risk factors. In Spain and Switzerland - as expected given the results in Table VII - the return becomes slightly weaker compared to the unconditional no-media premium. In Italy and Denmark the return premiums become positive (for the original unconditional long-short strategy they were insignificantly negative), although not significantly so.

[56]This is the case in the U.S., the UK, Japan, Australia, Hongkong, New Zealand, Singapore, Italy and Sweden.

Table VIII. Market State Based Media Strategy Returns Across Countries. At the end of each month t, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. The resulting returns are evaluated against widely accepted risk factors. Time-series means and factor alphas are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Regression Model	Long Leg	Short Leg	Long-Short
Panel 1: USA			
TS Mean	0.0149	0.0079	0.0070***
CAPM Alpha	0.0119***	0.0049**	0.0070***
FF Alpha	0.0085***	0.0015	0.0070***
Carhart Alpha	0.0087***	0.0017	0.0070***
Panel 2: Australia			
TS Mean	0.0216	0.0090	0.0126***
CAPM Alpha	0.0192	0.0066	0.0126***
FF Alpha	0.0244***	0.0117	0.0128***
Carhart Alpha	0.0336***	0.0202***	0.0133***
Panel 3: Hongkong			
TS Mean	0.0186	0.0063	0.0123***
CAPM Alpha	0.0085	-0.0031	0.0116**
FF Alpha	0.0032*	-0.0083***	0.0115***
Carhart Alpha	0.0038**	-0.0074***	0.0111***
Panel 4: Japan			
TS Mean	0.0068	0.0041	0.0027*
CAPM Alpha	0.0073***	0.0046**	0.0027**
FF Alpha	0.0039***	0.0003	0.0035***
Carhart Alpha	0.0038***	0.0002	0.0036***
Panel 5: NewZealand			
TS Mean	0.0191	0.0092	0.0099**
CAPM Alpha	0.0115**	0.0012	0.0103**
FF Alpha	0.0129**	0.0016	0.0113**
Carhart Alpha	0.0137**	0.0020	0.0116**
Panel 6: Singapore			
TS Mean	0.0140	0.0085	0.0055**
CAPM Alpha	0.0051**	-0.0002	0.0054***
FF Alpha	0.0031*	-0.0019	0.0050**
Carhart Alpha	0.0037*	-0.0015	0.0051**
Panel 7: UK			
TS Mean	0.0067	-0.0019	0.0086***
CAPM Alpha	0.0032	-0.0052	0.0084***
FF Alpha	0.0100	0.0018	0.0082***
Carhart Alpha	0.0157***	0.0074	0.0084***
Panel 8: Germany			
TS Mean	0.0059	0.0053	0.0006
CAPM Alpha	0.0050	0.0042	0.0007
FF Alpha	0.0124	0.0093	0.0031
Carhart Alpha	0.0220***	0.0167***	0.0053*
Panel 9: France			
TS Mean	0.0130	0.0060	0.0070**
CAPM Alpha	0.0127	0.0053	0.0074***
FF Alpha	0.0187***	0.0107**	0.0080***
Carhart Alpha	0.0204***	0.0124***	0.0080***
Panel 10: Switzerland			
TS Mean	0.0091	0.0044	0.0047*
CAPM Alpha	0.0109	0.0061	0.0048**
FF Alpha	0.0124**	0.0074	0.0051**
Carhart Alpha	0.0163***	0.0100**	0.0064***
Panel 11: Spain			
TS Mean	0.0086	0.0035	0.0051
CAPM Alpha	0.0039	-0.0005	0.0044*
FF Alpha	0.0032	-0.0008	0.0040*
Carhart Alpha	0.0051**	0.0009	0.0042*

Table VIII. Market State Based Media Strategy Returns Across Countries - Continued

Regression Model	Long Leg	Short Leg	Long-Short
Panel 12: Sweden			
TS Mean	0.0104	0.0034	0.0070**
CAPM Alpha	0.0087	0.0018	0.0069**
FF Alpha	0.0121	0.0050	0.0071**
Carhart Alpha	0.0162**	0.0094	0.0068*
Panel 13: Netherlands			
TS Mean	0.0090	0.0054	0.0035
CAPM Alpha	0.0053	0.0014	0.0040
FF Alpha	0.0052*	0.0011	0.0041
Carhart Alpha	0.0052*	0.0011	0.0041
Panel 14: Belgium			
TS Mean	0.0085	0.0088	-0.0003
CAPM Alpha	0.0045*	0.0050**	-0.0006
FF Alpha	0.0016	0.0026	-0.0010
Carhart Alpha	0.0018	0.0026	-0.0007
Panel 15: Norway			
TS Mean	0.0100	0.0080	0.0019
CAPM Alpha	-0.0022	-0.0026	0.0004
FF Alpha	-0.0030	-0.0025	-0.0005
Carhart Alpha	-0.0008	-0.0012	0.0004
Panel 16: Italy			
TS Mean	0.0020	-0.0006	0.0026
CAPM Alpha	0.0032	0.0003	0.0029
FF Alpha	0.0029	0.0004	0.0025
Carhart Alpha	0.0065	0.0046	0.0019
Panel 17: Finland			
TS Mean	0.0077	0.0079	-0.0002
CAPM Alpha	0.0031	0.0037	-0.0006
FF Alpha	0.0033	0.0023	0.0010
Carhart Alpha	0.0039	0.0017	0.0022
Panel 18: Austria			
TS Mean	0.0097	0.0107	-0.0010
CAPM Alpha	0.0011	0.0037	-0.0026
FF Alpha	0.0008	0.0034	-0.0026
Carhart Alpha	0.0019	0.0035	-0.0016
Panel 19: Denmark			
TS Mean	0.0107	0.0096	0.0011
CAPM Alpha	0.0062*	0.0056	0.0007
FF Alpha	0.0027	0.0042	-0.0015
Carhart Alpha	0.0032	0.0037	-0.0005
Panel 20: Greece			
TS Mean	-0.0050	-0.0052	0.0002
CAPM Alpha	-0.0106*	-0.0099*	-0.0007
FF Alpha	-0.0154**	-0.0151**	-0.0003
Carhart Alpha	-0.0115	-0.0112*	-0.0003

Overall, employing market states as a signal yields positive returns on average in all countries in our sample, but Belgium, Finland and Austria (all with small stock market capitalizations). In countries with large stock markets, the resulting return premiums are strongest and most significant.[57]

Forming an equal-weighted portfolio of the market state signal based long-short strategy across all countries yields an annualized Sharpe ratio of 0.9104 (two-sided p-value 0.92%). An equal-

[57] Our 20 countries in order of their stock market capitalization: USA, Japan, the UK, France, Germany, Australia, Hongkong, Switzerland, Spain, the Netherlands, Sweden, Italy, Singapore, Belgium, Norway, Denmark, Finland, Austria, New Zealand, Greece.

weighted portfolio across all countries of the standard strategy that is always long no-media and short high-media coverage stocks on the other hand results in a much lower annualized Sharpe ratio of 0.5043 (two-sided p-value 3.21%). This indicates that the market state signal based strategy considerably outperforms the original media coverage strategy and provides further evidence suggesting that state dependency plays an important role in explaining the relation between stock returns and mass media coverage.

Table IX contains the market state signal based strategy returns for portfolio holding periods ranging from 1 to 12 months for the countries with a significant return premium at the one-month horizon. As can be seen, the positive return premiums that we find at the one-month horizon always extend in a highly significant and consistent manner to all considered holding periods. Hence, this strategy yields return premiums that are be stable and persistent across different portfolio holding periods.

In Section A.5 in the Appendix we present tables containing the premiums resulting from applying our signal-based strategy to subsamples of stocks, formed according to different firm properties and illiquidity measures. The tables contain the resulting risk-adjusted returns (alphas) for the countries with a significant premium at the one-month horizon.

Within the terciles formed according to market capitalization, we find the return premium to be strongest among small caps in the U.S. and Japan. In the remaining markets, the premium is strongest, both in terms of magnitude and significance, among the stocks with the largest market value. Within market-to-book value sorts, there is a tendency towards medium and large market-to-book value terciles exhibiting the largest strategy returns. But in general, we find positive and often significant strategy returns across all market-to-book value terciles in the vast majority of countries. This is also the case for the sorts with respect to current month and past year returns: The resulting return premia are consistently positive across all terciles and mostly significant. Most importantly, we find the strategy returns to be largest and most significant among the most liquid sets of stocks (those with high price, low bid-ask spread, high volume and low Amihud illiquidity ratio). The only exception to this is Singapore, where the returns are by trend larger among illiquid stocks.

Table IX. Market State Based Media Strategy Returns Across Countries - Longer Holding Periods. At the end of each month t, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held from t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. The resulting returns are evaluated against widely accepted risk factors. Time-series means and factor alphas are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: USA				
1 month	0.0070***	0.0070***	0.0070***	0.0070***
3 months	0.0060***	0.0059***	0.0057***	0.0057***
6 months	0.0054***	0.0054***	0.0053***	0.0052***
9 months	0.0053***	0.0052***	0.0051***	0.0050***
12 months	0.0051***	0.0050***	0.0048***	0.0048***
Panel 2: Australia				
1 month	0.0126***	0.0126***	0.0128***	0.0133***
3 months	0.0115***	0.0115***	0.0119***	0.0121***
6 months	0.0120***	0.0119***	0.0124***	0.0124***
9 months	0.0116***	0.0116***	0.0120***	0.0120***
12 months	0.0115***	0.0115***	0.0118***	0.0118***
Panel 3: Hongkong				
1 month	0.0123***	0.0116**	0.0115***	0.0111***
3 months	0.0134***	0.0126***	0.0122***	0.0119***
6 months	0.0135***	0.0127**	0.0122***	0.0114***
9 months	0.0139***	0.0130***	0.0126***	0.0116***
12 months	0.0135***	0.0127**	0.0122***	0.0110***
Panel 4: Japan				
1 month	0.0027*	0.0027**	0.0035***	0.0036***
3 months	0.0016	0.0016	0.0020*	0.0020*
6 months	0.0015	0.0016	0.0018	0.0018*
9 months	0.0013	0.0013	0.0016	0.0016
12 months	0.0014	0.0015	0.0017	0.0018
Panel 5: New Zealand				
1 month	0.0099**	0.0103**	0.0113**	0.0116**
3 months	0.0082**	0.0090**	0.0098**	0.0107**
6 months	0.0062*	0.0068**	0.0069*	0.0078*
9 months	0.0058	0.0064*	0.0060	0.0071*
12 months	0.0042	0.0047	0.0041	0.0055
Panel 6: Singapore				
1 month	0.0055**	0.0054***	0.0050**	0.0051**
3 months	0.0054**	0.0051***	0.0047***	0.0051***
6 months	0.0056**	0.0053***	0.0049***	0.0053***
9 months	0.0055**	0.0052***	0.0047***	0.0052***
12 months	0.0056**	0.0053***	0.0047**	0.0052***
Panel 7: UK				
1 month	0.0086***	0.0084***	0.0082***	0.0084***
3 months	0.0078***	0.0076***	0.0075***	0.0078***
6 months	0.0076***	0.0074***	0.0073***	0.0075***
9 months	0.0070***	0.0068***	0.0068***	0.0069***
12 months	0.0068***	0.0066***	0.0066***	0.0067***

Table IX. Market State Based Media Strategy Returns Across Countries - Longer Holding Periods - Continued

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
		Panel 8: France		
1 month	0.0070**	0.0074***	0.0080***	0.0080***
3 months	0.0069**	0.0072***	0.0079***	0.0079***
6 months	0.0069***	0.0072***	0.0078***	0.0078***
9 months	0.0068***	0.0071***	0.0078***	0.0078***
12 months	0.0066***	0.0070***	0.0076***	0.0076***
		Panel 9: Switzerland		
1 month	0.0047*	0.0048**	0.0051**	0.0064***
3 months	0.0033	0.0034	0.0036*	0.0048**
6 months	0.0032	0.0033	0.0036*	0.0046**
9 months	0.0030	0.0031	0.0033	0.0043**
12 months	0.0034	0.0035	0.0036*	0.0046**
		Panel 10: Spain		
1 month	0.0051	0.0044*	0.0040*	0.0042*
3 months	0.0051	0.0041*	0.0037*	0.0040*
6 months	0.0049*	0.0044**	0.0041**	0.0044**
9 months	0.0048*	0.0045**	0.0043**	0.0046**
12 months	0.0045	0.0045**	0.0044**	0.0047**
		Panel 11: Sweden		
1 month	0.0070**	0.0069**	0.0071**	0.0068*
3 months	0.0077**	0.0076***	0.0073**	0.0068*
6 months	0.0094***	0.0093***	0.0089***	0.0084**
9 months	0.0090***	0.0089***	0.0084***	0.0081**
12 months	0.0094***	0.0093***	0.0088***	0.0085**

Alltogether, the return premiums resulting from the market state signal based strategy are well-behaved in the considered countries.[58] The premiums are highly persistent: In large stock markets, they are significantly positive and stable for portfolio holding periods well beyond the one-month horizon. Moreover, we consistently find positive return premiums across most firm characteristic terciles in all considered stock markets, and they are often statistically significant.

5 Conclusion

Employing a new measure of mass media coverage which also comprises internet news sources and that is conveniently obtained from the Bloomberg News Trend database, we analyze the relation between mass media coverage and the cross-section of stock returns in 20 developed countries with large stock markets. Focusing on a more recent and longer time period and extending the

[58]Opposed to the results we get when analyzing the unconditional no-high media coverage portfolio returns within subgroups of stocks.

analysis to a larger set of U.S. stocks, covering the entire NYSE and NASDAQ stock universe, we find unconditional results for the U.S. stock market that are qualitatively similar to the findings of Fang and Peress (2009): Stocks neglected by mass media earn a statistically significant and economically important return premium compared to stocks that are highly covered by mass media (positive media effect).

Internationally, only seven additional stock markets (Hongkong, France, Switzerland, Spain, the Netherlands, Belgium and Austria) exhibit a positive media effect that is statistically significant after controlling for common risk factors and economically large. In the UK, we find a large and significant negative media effect. Among small and illiquid stocks and among loser stocks with low current month returns we find a positive media effect in most countries, suggesting that the role of mass media is especially important for these subsets of stocks.

Most importantly, we provide evidence indicating that the relation between mass media coverage and the cross-section of stock returns in most markets depends on whether the market state is good or bad. When we condition on the market state being good, we find a positive, mostly economically large media effect in the vast majority of countries: Portfolios containing stocks that are not covered by mass media during good market state months subsequently clearly outperform portfolios containing stocks that are highly covered during good market months. For large stock markets, this effect is most pronounced. Conditional on the market state being bad on the other hand, we find much smaller and mostly insignificant or negative media effects.

Utilizing the state of the market as an out-of-sample signal, we evaluate the returns on a strategy that is long (short) stocks not covered and short (long) stocks highly covered by mass media when the market state is good (bad). The resulting return premiums turn out to be positive in 17 out of 20 countries. Among the countries with the largest stock market capitalizations, we find the premiums to be statistically highly significant even after controlling for well-known risk factors, to remain significant for portfolio holding periods up to 12 months, and to be stable and well-behaved when evaluated within various subgroups of stocks, formed according to important firm characteristics and liquidity proxies. The strategy returns are largest and most significant among the most liquid stocks.

REFERENCES

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31 – 56.

Antweiler, W., and M. Z. Fank, 2004, Is all that talk just noise? The information content of internet stock message boards, *Journal of Finance* 59, 1259–1294.

Barber, B., and T. Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets?, *Review of Financial Studies* 22, 151–186.

Chan, W., 2003, Stock price reaction to news and no-news: Drift and reversal after headlines, *Journal of Financial Economics* 70, 223–260.

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *The Journal of Finance* 57, 985–1019.

Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market states and momentum, *The Journal of Finance* 59, 1345–1365.

Engelberg, Joseph E., and Christopher A. Parsons, 2011, The causal impact of media in financial markets, *The Journal of Finance* 66, 67–97.

Fama, E.F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

——— , and K.R. French, 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457–472.

Fang, L., and J. Peress, 2009, Media coverage and the cross-section of stock returns, *Journal of Finance* 64, 2023—-2052.

Frieder, L., and A. Subrahmanyam, 2005, Brand preceptions and the market for common stock, *Journal of Financial and Quantitative Analysis* 40, 57–85.

Grullon, G., G. Kanatas, and J. P. Weston, 2004, Advertising, breadth of ownership, and liquidity, *Review of Financial Studies* 17, 439–461.

Harris, L.E., 1994, Minimum price variations, discrete bid-ask spreads, and quotation sizes, *Review of Financial Studies* 7, 149–178.

He, Y., 2013, Decimal trading in the U.S. stock markets, *Encyclopedia of Finance*.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65—-91.

Kothari, S.P., Jonathan Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics* 79, 537 – 568.

Lakonishok, J, and I Lee, 2001, Are insider trades informative?, *Review of Financial Studies* 14, 79–11.

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483—-510.

Meschke, F. J., 2004, CEO interviews on CNBC, Working Paper, Arizona State University.

Schmidt, P., U. Von Arx, A. Wagner, and A. Ziegler, 2011, On the construction of common size, value and momentum factors in international stock markets: A guide with applications, Swiss Finance Institute Research Paper No. 10-58.

Tetlock, P., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

——— , 2010, Does public financial news resolve asymmetric information, *Review of Financial Studies* 23, 3520–3557.

——— , 2011, All the news that's fit to reprint: Do investors react to stale information?, *Review of Financial Studies* 24, 1481–1512.

——— , M. Saar-Tschansky, and S. Macskassy, 2008, More than words: Quantifying language to measure firms' fundamentals, *Journal of Finance* 63, 1437–1467.

Xu, Y., and B.G. Malkiel, 2003, Investigating the bahavior of idiosyncratic volatility, *Journal of Business* 76, 613—-645.

APPENDIX

A Appendix

A.1 Data

Variable	Type	Description
		I. Media Coverage Variables
Media Coverage	Cross-Section & monthly time series	Total number of articles with high relevance published about the firm during a month t. Higher numbers imply high media coverage for the firm. Source: Bloomberg News Trend.
		II. Financial Variables
MV	Cross-section & monthly time series	Market Capitalization .... . Source: Bloomberg.
MTBVyearly	Cross-section & yearly time series	Monthly market price to book value ratios per share at the previous year end. Source: Bloomberg
RETpastyear	Cross-section & monthly time series	Return realized over previous year.
RETcurrentmonth	Cross-section & monthly time series	Monthly return realized at month t.
Pavgpast	Cross-section & monthly time series	Average closing price during previous month.
BidAskSpread	Cross-section & monthly time series	Monthly $\frac{(BidPrice-AskPrice)}{2}$, employing the bid and ask prices at the end of each month.
VAavgpastyear	Cross-section & yearly time series	Average Trading Volume by value over the last year.
Amihud	Cross-section & yearly time series	Amihud's Illiquidity Ratio: Absolute return divided by daily trading volume.

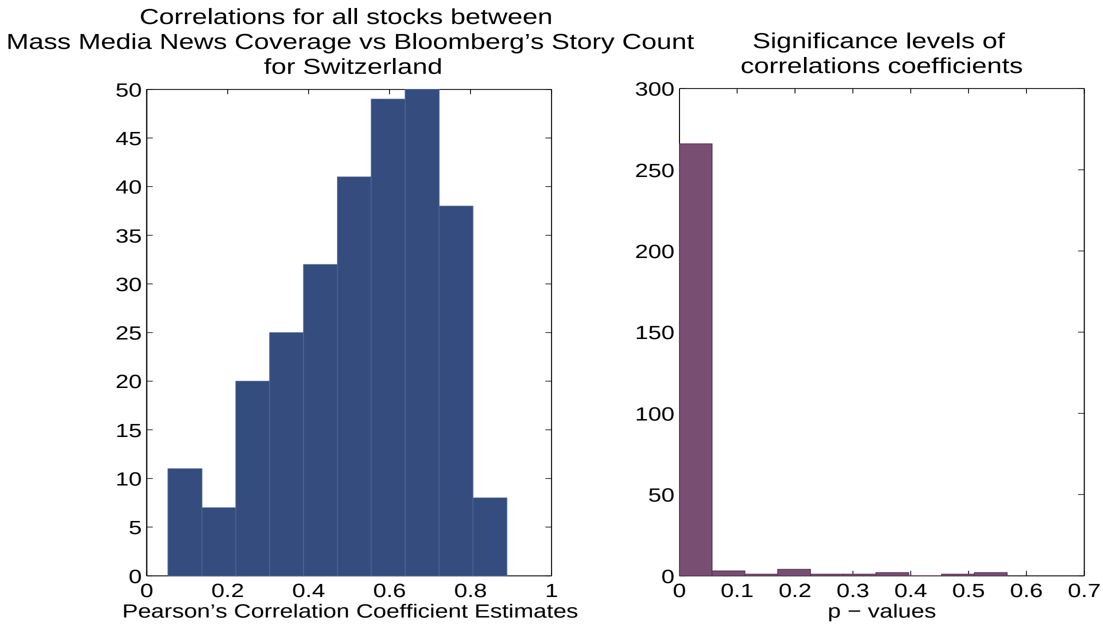


Figure 1. Pearson's Correlation Coefficient Estimates between Factiva mass media coverage and Bloomberg's Worldwide media coverage

A.2 Unconditional Results for all Formation and Holding Periods

Table I. Media Premiums in Austria. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0044	0.0079**	0.0077**	0.0074**
3 months	0.0040	0.0072***	0.0066***	0.0065***
6 months	0.0018	0.0055**	0.0050**	0.0048**
9 months	0.0011	0.0044*	0.0039*	0.0038*
12 months	0.0007	0.0042*	0.0037*	0.0035*
Panel 2: Formation Period = 3 Months				
1 month	0.0055	0.0094**	0.0091***	0.0089***
3 months	0.0039	0.0075***	0.0071***	0.0068***
6 months	0.0019	0.0057**	0.0053**	0.0050**
9 months	0.0009	0.0046*	0.0042*	0.0039*
12 months	0.0003	0.0044*	0.0040*	0.0036
Panel 3: Formation Period = 6 Months				
1 month	0.0047	0.0090***	0.0086***	0.0081***
3 months	0.0034	0.0072**	0.0067**	0.0063**
6 months	0.0014	0.0057**	0.0052**	0.0048*
9 months	0.0007	0.0049*	0.0045*	0.0042*
12 months	0.0007	0.0049*	0.0045*	0.0041*
Panel 4: Formation Period = 9 Months				
1 month	0.0052	0.0096***	0.0092***	0.0089***
3 months	0.0030	0.0070**	0.0065**	0.0061**
6 months	0.0012	0.0056*	0.0051*	0.0048*
9 months	0.0009	0.0052*	0.0047*	0.0043*
12 months	0.0005	0.0048*	0.0043	0.0039
Panel 5: Formation Period = 12 Months				
1 month	0.0040	0.0091**	0.0084***	0.0081***
3 months	0.0022	0.0068**	0.0061**	0.0058**
6 months	0.0009	0.0057**	0.0051*	0.0046*
9 months	0.0004	0.0052*	0.0046*	0.0042
12 months	-0.0003	0.0046	0.0039	0.0035

Table II. Media Premiums in Belgium. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0089***	0.0100***	0.0098***	0.0086***
3 months	0.0039	0.0050***	0.0052***	0.0034*
6 months	0.0022	0.0033*	0.0037**	0.0019
9 months	0.0023	0.0033*	0.0034**	0.0018
12 months	0.0023	0.0033*	0.0033*	0.0018
Panel 2: Formation Period = 3 Months				
1 month	0.0067*	0.0083***	0.0086***	0.0071***
3 months	0.0025	0.0040*	0.0043**	0.0028
6 months	0.0006	0.0020	0.0024	0.0008
9 months	0.0006	0.0019	0.0022	0.0006
12 months	0.0005	0.0018	0.0018	0.0003
Panel 3: Formation Period = 6 Months				
1 month	0.0068*	0.0086***	0.0089***	0.0072***
3 months	0.0015	0.0032	0.0037	0.0017
6 months	-0.0001	0.0016	0.0020	0.0000
9 months	-0.0003	0.0012	0.0015	-0.0002
12 months	0.0002	0.0017	0.0018	0.0002
Panel 4: Formation Period = 9 Months				
1 month	0.0058	0.0078***	0.0079***	0.0059**
3 months	0.0013	0.0032	0.0035	0.0015
6 months	0.0001	0.0019	0.0021	0.0003
9 months	0.0001	0.0018	0.0018	0.0002
12 months	0.0006	0.0022	0.0021	0.0006
Panel 5: Formation Period = 12 Months				
1 month	0.0045	0.0069***	0.0077***	0.0049*
3 months	-0.0001	0.0023	0.0031	0.0006
6 months	-0.0013	0.0009	0.0017	-0.0008
9 months	-0.0013	0.0009	0.0015	-0.0007
12 months	-0.0007	0.0014	0.0019	-0.0003

Table III. Media Premiums in France. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0074**	0.0067***	0.0056***	0.0056***
3 months	0.0038	0.0032*	0.0022	0.0022
6 months	0.0023	0.0017	0.0008	0.0007
9 months	0.0023	0.0017	0.0009	0.0008
12 months	0.0022	0.0017	0.0008	0.0008
Panel 2: Formation Period = 3 Months				
1 month	0.0064**	0.0056***	0.0048***	0.0048***
3 months	0.0024	0.0016	0.0009	0.0009
6 months	0.0012	0.0004	-0.0001	-0.0002
9 months	0.0013	0.0005	-0.0001	-0.0001
12 months	0.0011	0.0004	-0.0002	-0.0002
Panel 3: Formation Period = 6 Months				
1 month	0.0057*	0.0045**	0.0036**	0.0035**
3 months	0.0022	0.0010	0.0004	0.0003
6 months	0.0011	-0.0000	-0.0006	-0.0006
9 months	0.0011	-0.0000	-0.0006	-0.0006
12 months	0.0012	0.0001	-0.0004	-0.0005
Panel 4: Formation Period = 9 Months				
1 month	0.0055*	0.0039*	0.0032*	0.0032*
3 months	0.0022	0.0006	0.0001	0.0001
6 months	0.0009	-0.0007	-0.0010	-0.0011
9 months	0.0010	-0.0006	-0.0009	-0.0010
12 months	0.0013	-0.0002	-0.0005	-0.0006
Panel 5: Formation Period = 12 Months				
1 month	0.0051	0.0037*	0.0033*	0.0032*
3 months	0.0015	0.0002	-0.0002	-0.0003
6 months	0.0005	-0.0008	-0.0010	-0.0011
9 months	0.0005	-0.0007	-0.0010	-0.0011
12 months	0.0007	-0.0005	-0.0008	-0.0009

Table IV. Media Premiums in the Netherlands. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0067**	0.0069***	0.0060**	0.0059**
3 months	0.0067**	0.0071***	0.0066***	0.0066***
6 months	0.0041	0.0045**	0.0038*	0.0037*
9 months	0.0032	0.0036*	0.0029	0.0029
12 months	0.0033	0.0036*	0.0029	0.0029
Panel 2: Formation Period = 3 Months				
1 month	0.0056	0.0064***	0.0056	0.0056*
3 months	0.0068	0.0080**	0.0077**	0.0077**
6 months	0.0032	0.0040*	0.0031	0.0031
9 months	0.0030	0.0034	0.0026	0.0026
12 months	0.0028	0.0032	0.0025	0.0025
Panel 3: Formation Period = 6 Months				
1 month	0.0081*	0.0088***	0.0078***	0.0078***
3 months	0.0065	0.0072**	0.0069**	0.0069**
6 months	0.0037	0.0043*	0.0036	0.0036
9 months	0.0032	0.0035	0.0030	0.0030
12 months	0.0027	0.0031	0.0026	0.0026
Panel 4: Formation Period = 9 Months				
1 month	0.0076	0.0083**	0.0080**	0.0079**
3 months	0.0061	0.0068*	0.0069	0.0069
6 months	0.0029	0.0032	0.0027	0.0026
9 months	0.0024	0.0024	0.0019	0.0018
12 months	0.0025	0.0025	0.0019	0.0019
Panel 5: Formation Period = 12 Months				
1 month	0.0055	0.0059*	0.0051	0.0050
3 months	0.0051	0.0057	0.0056	0.0053
6 months	0.0013	0.0017	0.0008	0.0006
9 months	0.0011	0.0014	0.0006	0.0004
12 months	0.0012	0.0014	0.0007	0.0006

Table V. Media Premiums in Spain. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0052	0.0063**	0.0063***	0.0062**
3 months	0.0039	0.0047*	0.0045*	0.0044*
6 months	0.0027	0.0035	0.0034	0.0033
9 months	0.0018	0.0027	0.0026	0.0025
12 months	0.0014	0.0022	0.0022	0.0021
Panel 2: Formation Period = 3 Months				
1 month	0.0038	0.0042**	0.0041	0.0037
3 months	0.0038	0.0042	0.0040	0.0038
6 months	0.0026	0.0031	0.0030	0.0029
9 months	0.0015	0.0025	0.0024	0.0023
12 months	0.0013	0.0021	0.0021	0.0020
Panel 3: Formation Period = 6 Months				
1 month	0.0034	0.0043	0.0044	0.0039
3 months	0.0030	0.0039	0.0040	0.0038
6 months	0.0015	0.0028	0.0028	0.0027
9 months	0.0011	0.0023	0.0024	0.0023
12 months	0.0010	0.0021	0.0022	0.0022
Panel 4: Formation Period = 9 Months				
1 month	0.0036	0.0041	0.0042	0.0039
3 months	0.0028	0.0037	0.0039	0.0035
6 months	0.0015	0.0024	0.0025	0.0022
9 months	0.0012	0.0023	0.0024	0.0021
12 months	0.0010	0.0020	0.0022	0.0019
Panel 5: Formation Period = 12 Months				
1 month	0.0040	0.0052*	0.0049*	0.0046
3 months	0.0031	0.0046	0.0043	0.0041
6 months	0.0021	0.0036	0.0034	0.0032
9 months	0.0017	0.0033	0.0032	0.0030
12 months	0.0016	0.0032	0.0031	0.0029

Table VI. Media Premiums in Switzerland. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0051*	0.0046**	0.0044**	0.0038**
3 months	0.0049*	0.0044**	0.0043***	0.0036**
6 months	0.0039	0.0035*	0.0034**	0.0028**
9 months	0.0032	0.0028	0.0027**	0.0021
12 months	0.0027	0.0023	0.0022*	0.0017
Panel 2: Formation Period = 3 Months				
1 month	0.0049	0.0044**	0.0050**	0.0041*
3 months	0.0049	0.0045*	0.0049**	0.0041**
6 months	0.0036	0.0031	0.0036*	0.0027
9 months	0.0033	0.0028	0.0032*	0.0023
12 months	0.0027	0.0022	0.0027	0.0019
Panel 3: Formation Period = 6 Months				
1 month	0.0044	0.0034	0.0035*	0.0026
3 months	0.0042	0.0032	0.0032	0.0024
6 months	0.0034	0.0025	0.0025	0.0016
9 months	0.0028	0.0019	0.0018	0.0010
12 months	0.0024	0.0015	0.0015	0.0007
Panel 4: Formation Period = 9 Months				
1 month	0.0049	0.0035	0.0033	0.0025
3 months	0.0049	0.0035	0.0033	0.0025
6 months	0.0040	0.0026	0.0025	0.0018
9 months	0.0035	0.0022	0.0021	0.0014
12 months	0.0033	0.0020	0.0020	0.0014
Panel 5: Formation Period = 12 Months				
1 month	0.0028	0.0015	0.0015	0.0006
3 months	0.0034	0.0021	0.0021	0.0012
6 months	0.0029	0.0016	0.0017	0.0008
9 months	0.0027	0.0014	0.0015	0.0007
12 months	0.0028	0.0015	0.0015	0.0008

Table VII. Media Premiums in the UK. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	-0.0047**	-0.0044**	-0.0034*	-0.0028
3 months	-0.0041**	-0.0038**	-0.0030*	-0.0026
6 months	-0.0040**	-0.0037**	-0.0030**	-0.0027*
9 months	-0.0035*	-0.0032*	-0.0026*	-0.0022
12 months	-0.0037**	-0.0035**	-0.0028**	-0.0024*
Panel 2: Formation Period = 3 Months				
1 month	-0.0063***	-0.0058**	-0.0046***	-0.0042**
3 months	-0.0061***	-0.0056***	-0.0045**	-0.0044**
6 months	-0.0062***	-0.0057***	-0.0046***	-0.0045**
9 months	-0.0052**	-0.0047***	-0.0037**	-0.0035**
12 months	-0.0057***	-0.0052***	-0.0043***	-0.0040***
Panel 3: Formation Period = 6 Months				
1 month	-0.0079***	-0.0077***	-0.0066***	-0.0065***
3 months	-0.0075***	-0.0073***	-0.0062***	-0.0062***
6 months	-0.0066***	-0.0064***	-0.0055***	-0.0054***
9 months	-0.0062***	-0.0059***	-0.0051***	-0.0049***
12 months	-0.0057***	-0.0055***	-0.0047***	-0.0044***
Panel 4: Formation Period = 9 Months				
1 month	-0.0084***	-0.0084***	-0.0071***	-0.0071***
3 months	-0.0078***	-0.0078***	-0.0066***	-0.0067***
6 months	-0.0074***	-0.0074***	-0.0063***	-0.0063***
9 months	-0.0065***	-0.0065***	-0.0054***	-0.0053***
12 months	-0.0060***	-0.0060***	-0.0049***	-0.0047***
Panel 5: Formation Period = 12 Months				
1 month	-0.0094***	-0.0092***	-0.0081***	-0.0081***
3 months	-0.0088***	-0.0086***	-0.0076***	-0.0076***
6 months	-0.0076***	-0.0074***	-0.0064***	-0.0064***
9 months	-0.0066***	-0.0064***	-0.0054***	-0.0053***
12 months	-0.0060***	-0.0058***	-0.0048***	-0.0045**

Table VIII. Media Premiums in Hongkong. This Table reports the returns on a zero-investment portfolio that goes long stocks with No media coverage over the last k months and short stocks with High media coverage over the last k months (formation period), with $k = 1, 3, 6, 9, 12$. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Time-series means plus alpha estimates resulting from regressing the monthly long-short portfolio returns on widely accepted risk factors are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	TS Mean	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: Formation Period = 1 Month				
1 month	0.0095**	0.0107**	0.0086***	0.0071***
3 months	0.0103***	0.0116**	0.0102***	0.0084***
6 months	0.0098**	0.0111**	0.0097***	0.0077***
9 months	0.0098**	0.0111**	0.0097***	0.0075***
12 months	0.0095**	0.0108**	0.0094***	0.0073***
Panel 2: Formation Period = 3 Months				
1 month	0.0097***	0.0109**	0.0114***	0.0103***
3 months	0.0087**	0.0099**	0.0109***	0.0098***
6 months	0.0083**	0.0096**	0.0105***	0.0092***
9 months	0.0078**	0.0091**	0.0103***	0.0089***
12 months	0.0076**	0.0089**	0.0101***	0.0086***
Panel 3: Formation Period = 6 Months				
1 month	0.0088**	0.0103**	0.0109***	0.0095***
3 months	0.0083**	0.0100**	0.0108***	0.0092***
6 months	0.0081**	0.0098**	0.0109***	0.0090***
9 months	0.0078**	0.0096**	0.0109***	0.0087***
12 months	0.0077**	0.0094**	0.0107***	0.0083***
Panel 4: Formation Period = 9 Months				
1 month	0.0098***	0.0114**	0.0111***	0.0092***
3 months	0.0091**	0.0107**	0.0110***	0.0086***
6 months	0.0092**	0.0108**	0.0114***	0.0086***
9 months	0.0087**	0.0104**	0.0110***	0.0080***
12 months	0.0087**	0.0103**	0.0109***	0.0078***
Panel 5: Formation Period = 12 Months				
1 month	0.0095**	0.0114**	0.0111***	0.0086***
3 months	0.0092**	0.0112**	0.0113***	0.0085***
6 months	0.0093**	0.0113**	0.0115***	0.0083***
9 months	0.0091**	0.0111**	0.0114***	0.0080***
12 months	0.0091**	0.0111**	0.0113***	0.0078***

A.3 Current Month Losers and Winners: Double-Sort Results across Countries

Table IX. Media Premiums for Current Month Losers. This table reports the Carhart-alphas on equally weighted No minus High media coverage (No-High) portfolios formed among stocks in the lowest current month return tercile. At the end of each month t we first sort all stocks into terciles according to their returns during month t. Within the low current month return tercile, we form portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. The High portfolio contains the stocks with media coverage higher than the median media coverage in month t. The portfolios are held from t to $t+k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Carhart-alpha estimates from regressing the monthly returns on the No, on the High and on the No-High portfolio on Carhart factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	No Media	High Media	No-High
	Formation Period = 1 Month		
	Panel 1: USA		
1 month	0.0151***	0.0048**	0.0103***
3 months	0.0098***	0.0043**	0.0055***
6 months	0.0083***	0.0037**	0.0046***
9 months	0.0073***	0.0037**	0.0036**
12 months	0.0069***	0.0034**	0.0035**
	Panel 2: Australia		
1 month	0.0453***	0.0173**	0.0280***
3 months	0.0295***	0.0184***	0.0111***
6 months	0.0272***	0.0235***	0.0037
9 months	0.0266***	0.0252***	0.0014
12 months	0.0265***	0.0250***	0.0015
	Panel 3: Hongkong		
1 month	0.0035	-0.0106*	0.0142***
3 months	0.0022	-0.0101***	0.0123***
6 months	0.0006	-0.0106***	0.0112***
9 months	0.0005	-0.0096***	0.0101***
12 months	0.0001	-0.0107***	0.0108***
	Panel 4: Japan		
1 month	0.0061***	0.0011	0.0050***
3 months	0.0028**	0.0010	0.0017
6 months	0.0029***	0.0012	0.0017
9 months	0.0026**	0.0015	0.0011
12 months	0.0021**	0.0011	0.0010
	Panel 5: NewZealand		
1 month	0.0203***	0.0000	0.0205***
3 months	0.0062	0.0071	-0.0022
6 months	0.0034	0.0071	-0.0049
9 months	0.0026	0.0061	-0.0060
12 months	0.0025	0.0093*	-0.0085
	Panel 6: Singapore		
1 month	0.0091***	-0.0029	0.0120***
3 months	-0.0004	-0.0024	0.0020
6 months	-0.0019	-0.0026	0.0008
9 months	-0.0010	-0.0023	0.0013
12 months	-0.0018	-0.0028	0.0010
	Panel 7: UK		
1 month	0.0103*	0.0081	0.0022
3 months	0.0097*	0.0084	0.0012
6 months	0.0100*	0.0116**	-0.0015
9 months	0.0112**	0.0120**	-0.0008
12 months	0.0115**	0.0128**	-0.0012
	Panel 8: Germany		
1 month	0.0369***	0.0177***	0.0192***
3 months	0.0213***	0.0143**	0.0070*
6 months	0.0169***	0.0154**	0.0015
9 months	0.0169***	0.0149**	0.0020
12 months	0.0163**	0.0154**	0.0009
	Panel 9: France		
1 month	0.0349***	0.0174***	0.0176***
3 months	0.0198***	0.0140***	0.0057***
6 months	0.0155***	0.0128***	0.0026
9 months	0.0144**	0.0123**	0.0021
12 months	0.0138**	0.0119**	0.0019

Table IX. Media Premiums for Current Month Losers - Continued

Holding Period	No Media	High Media	No-High
	Formation Period = 1 Month		
	Panel 10: Switzerland		
1 month	0.0167***	0.0097**	0.0070**
3 months	0.0141***	0.0108**	0.0032
6 months	0.0137***	0.0112**	0.0024
9 months	0.0141***	0.0114***	0.0026
12 months	0.0140***	0.0123***	0.0017
	Panel 11: Spain		
1 month	0.0067*	0.0027	0.0040
3 months	0.0051*	0.0017	0.0035
6 months	0.0037	0.0020	0.0017
9 months	0.0042	0.0021	0.0021
12 months	0.0033	0.0011	0.0022
	Panel 12: Sweden		
1 month	0.0248***	0.0106	0.0142***
3 months	0.0107	0.0084	0.0024
6 months	0.0073	0.0109	-0.0037
9 months	0.0069	0.0111	-0.0042
12 months	0.0083	0.0113	-0.0030
	Panel 13: Netherlands		
1 month	0.0064	-0.0044	0.0108**
3 months	0.0032	-0.0044	0.0076**
6 months	0.0023	-0.0029	0.0052
9 months	0.0003	-0.0023	0.0025
12 months	0.0004	-0.0023	0.0027
	Panel 14: Belgium		
1 month	0.0156***	-0.0036	0.0192***
3 months	0.0066***	-0.0057*	0.0122***
6 months	0.0017	-0.0033	0.0050*
9 months	0.0021	-0.0027	0.0047**
12 months	0.0017	-0.0022	0.0040*
	Panel 15: Norway		
1 month	0.0073	-0.0139**	0.0205**
3 months	-0.0008	-0.0100**	0.0064
6 months	-0.0013	-0.0039	-0.0000
9 months	-0.0007	-0.0030	-0.0006
12 months	-0.0005	-0.0029	0.0010
	Panel 16: Italy		
1 month	0.0094*	0.0032	0.0062*
3 months	0.0040	0.0050	-0.0010
6 months	0.0031	0.0047	-0.0016
9 months	0.0035	0.0032	0.0003
12 months	0.0029	0.0032	-0.0004
	Panel 17: Finland		
1 month	0.0136***	-0.0023	0.0159***
3 months	0.0037	-0.0008	0.0046
6 months	0.0017	-0.0001	0.0018
9 months	0.0032	0.0001	0.0026
12 months	0.0027	-0.0003	0.0023
	Panel 18: Austria		
1 month	0.0159***	-0.0111***	0.0270***
3 months	0.0069**	-0.0057**	0.0124***
6 months	0.0044*	-0.0052*	0.0088**
9 months	0.0039	-0.0034	0.0069**
12 months	0.0041	-0.0018	0.0059**
	Panel 19: Denmark		
1 month	0.0050	0.0027	0.0027
3 months	-0.0020	0.0014	-0.0043
6 months	-0.0015	-0.0037	0.0010
9 months	-0.0019	-0.0029	-0.0003
12 months	-0.0022	-0.0032	-0.0006
	Panel 20: Greece		
1 month	-0.0001	-0.0087	0.0106
3 months	-0.0077	-0.0114	0.0048
6 months	-0.0092	-0.0103	0.0051
9 months	-0.0115	-0.0073	0.0021
12 months	-0.0125	-0.0081	0.0036

Table X. Media Premiums for Current Month Winners. This table reports the Carhart-alphas on equally weighted No minus High media coverage (No-High) portfolios formed among stocks in the highest current month return tercile. At the end of each month t we first sort all stocks into terciles according to their returns during month t. Within the high current month return tercile, we form portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. The High portfolio contains the stocks with media coverage higher than the median media coverage in month t. The portfolios are held from t to $t + k$, with $k = 1, 3, 6, 9, 12$ months (holding period). We use the overlapping portfolio approach of Jegadeesh and Titman (1993) to calculate the returns. Carhart-alpha estimates from regressing the monthly returns on the No, on the High and on the No-High portfolio on Carhart factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Holding Period	No Media	High Media	No-High
Formation Period = 1 Month - Carhart Alphas			
Panel 1: USA			
1 month	-0.0002	0.0019	-0.0021
3 months	0.0042**	0.0013	0.0029*
6 months	0.0047***	0.0017	0.0030*
9 months	0.0055***	0.0016	0.0039**
12 months	0.0054***	0.0018*	0.0036**
Panel 2: Australia			
1 month	0.0157**	0.0247***	-0.0091***
3 months	0.0241***	0.0271***	-0.0029
6 months	0.0254***	0.0270***	-0.0016
9 months	0.0261***	0.0264***	-0.0003
12 months	0.0273***	0.0272***	0.0001
Panel 3: Hongkong			
1 month	0.0024	-0.0010	0.0034
3 months	0.0022	-0.0058**	0.0080***
6 months	0.0013	-0.0064**	0.0077***
9 months	0.0008	-0.0070**	0.0078***
12 months	0.0004	-0.0064**	0.0068***
Panel 4: Japan			
1 month	-0.0023	0.0018	-0.0041**
3 months	0.0005	0.0032***	-0.0027***
6 months	0.0008	0.0021**	-0.0012
9 months	0.0008	0.0024***	-0.0016*
12 months	0.0016*	0.0024***	-0.0008
Panel 5: NewZealand			
1 month	-0.0086**	0.0079*	-0.0156***
3 months	0.0013	0.0085**	-0.0064**
6 months	0.0035	0.0083*	-0.0043
9 months	0.0045	0.0092**	-0.0036
12 months	0.0054	0.0078*	-0.0013
Panel 6: Singapore			
1 month	-0.0094***	0.0069**	-0.0163***
3 months	-0.0023	0.0055**	-0.0078***
6 months	-0.0003	0.0031	-0.0034
9 months	-0.0011	0.0023	-0.0034
12 months	-0.0008	0.0024	-0.0031
Panel 7: UK			
1 month	0.0131**	0.0152***	-0.0021
3 months	0.0135**	0.0143***	-0.0008
6 months	0.0141**	0.0147***	-0.0006
9 months	0.0142**	0.0152***	-0.0010
12 months	0.0146**	0.0160***	-0.0014
Panel 8: Germany			
1 month	0.0096	0.0142**	-0.0046
3 months	0.0163**	0.0162**	0.0001
6 months	0.0181***	0.0174***	0.0008
9 months	0.0181***	0.0186***	-0.0005
12 months	0.0191***	0.0195***	-0.0004
Panel 9: France			
1 month	0.0076	0.0099*	-0.0023
3 months	0.0126**	0.0126**	0.0001
6 months	0.0139**	0.0137***	0.0001
9 months	0.0149**	0.0144***	0.0006
12 months	0.0157***	0.0150***	0.0007

Table X. Media Premiums for Current Month Winners - Continued

Holding Period	No Media	High Media	No-High
Formation Period = 1 Month - Carhart Alphas			
Panel 10: Switzerland			
1 month	0.0128***	0.0152***	-0.0024
3 months	0.0152***	0.0140***	0.0012
6 months	0.0160***	0.0140***	0.0021
9 months	0.0158***	0.0146***	0.0012
12 months	0.0162***	0.0148***	0.0014
Panel 11: Spain			
1 month	0.0093***	0.0021	0.0073**
3 months	0.0062*	0.0019	0.0043
6 months	0.0062**	0.0016	0.0046*
9 months	0.0053*	0.0017	0.0036
12 months	0.0053*	0.0022	0.0031
Panel 12: Sweden			
1 month	0.0026	0.0111	-0.0085*
3 months	0.0100	0.0114	-0.0014
6 months	0.0122	0.0110	0.0012
9 months	0.0127	0.0115	0.0012
12 months	0.0138	0.0120	0.0018
Panel 13: Netherlands			
1 month	0.0028	0.0049	-0.0021
3 months	0.0079***	0.0053*	0.0026
6 months	0.0063**	0.0041	0.0022
9 months	0.0069**	0.0035	0.0033
12 months	0.0077***	0.0043*	0.0034
Panel 14: Belgium			
1 month	-0.0004	0.0029	-0.0033
3 months	0.0006	0.0039	-0.0033
6 months	0.0021	0.0023	-0.0002
9 months	0.0018	0.0020	-0.0003
12 months	0.0020	0.0017	0.0003
Panel 15: Norway			
1 month	-0.0076	-0.0001	-0.0075*
3 months	0.0015	0.0001	0.0014
6 months	0.0014	-0.0000	0.0014
9 months	0.0007	-0.0005	0.0012
12 months	0.0009	-0.0004	0.0014
Panel 16: Italy			
1 month	0.0024	0.0069	-0.0046
3 months	0.0042	0.0054	-0.0012
6 months	0.0048	0.0054	-0.0007
9 months	0.0058	0.0057	0.0001
12 months	0.0060	0.0066	-0.0007
Panel 17: Finland			
1 month	-0.0090***	0.0031	-0.0123***
3 months	0.0010	0.0050	-0.0050*
6 months	0.0022	0.0038	-0.0026
9 months	0.0040	0.0041	-0.0014
12 months	0.0030	0.0042	-0.0019
Panel 18: Austria			
1 month	0.0015	0.0071*	-0.0056
3 months	0.0041	-0.0002	0.0043
6 months	0.0052**	0.0011	0.0041
9 months	0.0046*	0.0013	0.0033
12 months	0.0047*	0.0014	0.0039
Panel 19: Denmark			
1 month	-0.0030	0.0133**	-0.0167***
3 months	0.0003	0.0066	-0.0079**
6 months	0.0010	0.0048	-0.0057*
9 months	0.0011	0.0015	-0.0026
12 months	0.0016	0.0022	-0.0030
Panel 20: Greece			
1 month	-0.0213***	-0.0169**	-0.0042
3 months	-0.0170**	-0.0111**	-0.0060
6 months	-0.0170**	-0.0138***	-0.0042
9 months	-0.0160**	-0.0115**	-0.0045
12 months	-0.0164**	-0.0114**	-0.0050

A.4 Selected Double-Sort Results across Countries

Table XI. Media Premiums Conditional on Market Value. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to market capitalization. At the end of each month t we first sort all stocks into terciles according to their market value. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage		No-High	
MV	Low	Med	High
	Panel 1: USA		
TS Mean	-0.0017	-0.0044*	0.0018
CAPM Alpha	-0.0011	-0.0040*	0.0020
FF Alpha	-0.0007	-0.0049**	0.0010
CAR Alpha	-0.0011	-0.0050***	0.0008
	Panel 2: Australia		
TS Mean	0.0131	-0.0112	-0.0028
CAPM Alpha	0.0131	-0.0113	-0.0028
FF Alpha	0.0113	-0.0131	-0.0035
CAR Alpha	0.0160	-0.0131	-0.0026
	Panel 3: Hongkong		
TS Mean	0.0056	0.0031	0.0007
CAPM Alpha	0.0079	0.0049	0.0014
FF Alpha	0.0083	0.0064	-0.0001
CAR Alpha	0.0110	0.0053	-0.0016
	Panel 4: Japan		
TS Mean	0.0024	-0.0019	-0.0007
CAPM Alpha	0.0024	-0.0021	-0.0011
FF Alpha	0.0027	-0.0017	-0.0024*
CAR Alpha	0.0028	-0.0017	-0.0022**
	Panel 5: NewZealand		
TS Mean	0.0436**	-0.0056	-0.0052
CAPM Alpha	0.0442***	-0.0052	-0.0042
FF Alpha	0.0440***	-0.0040	-0.0061
CAR Alpha	0.0520***	-0.0027	-0.0078
	Panel 6: Singapore		
TS Mean	0.0098	0.0006	-0.0032
CAPM Alpha	0.0123*	0.0006	-0.0034
FF Alpha	0.0136*	-0.0017	-0.0034
CAR Alpha	0.0096	-0.0006	-0.0031
	Panel 7: UK		
TS Mean	0.0107**	-0.0022	-0.0002
CAPM Alpha	0.0110**	-0.0022	-0.0001
FF Alpha	0.0124**	-0.0034	0.0007
CAR Alpha	0.0114**	-0.0037	0.0012
	Panel 8: Germany		
TS Mean	0.0316**	0.0075	0.0025
CAPM Alpha	0.0312***	0.0074*	0.0025
FF Alpha	0.0250*	0.0028	0.0015
CAR Alpha	0.0249*	-0.0008	-0.0009
	Panel 9: France		
TS Mean	0.0148**	0.0038	0.0031
CAPM Alpha	0.0145**	0.0029	0.0025
FF Alpha	0.0132*	0.0022	0.0012
CAR Alpha	0.0127*	0.0011	0.0011

Table XI. Media Premiums Conditional on Market Value - Continued

Media Coverage	No-High		
MV	Low	Med	High
Panel 10: Switzerland			
TS Mean	0.0093**	0.0079**	0.0046
CAPM Alpha	0.0090*	0.0076*	0.0042*
FF Alpha	0.0072	0.0064*	0.0039*
CAR Alpha	0.0064	0.0052	0.0031
Panel 11: Spain			
TS Mean	0.0109	0.0082*	0.0048
CAPM Alpha	0.0131*	0.0086**	0.0053
FF Alpha	0.0117	0.0088**	0.0061
CAR Alpha	0.0101	0.0069	0.0048
Panel 12: Sweden			
TS Mean	0.0119	0.0003	0.0025
CAPM Alpha	0.0121*	0.0005	0.0027
FF Alpha	0.0104	-0.0021	0.0035
CAR Alpha	0.0119	-0.0038	0.0031
Panel 13: Netherlands			
TS Mean	0.0231***	0.0045	0.0048
CAPM Alpha	0.0248***	0.0049	0.0042
FF Alpha	0.0254***	0.0045	0.0010
CAR Alpha	0.0249***	0.0046	0.0009
Panel 14: Belgium			
TS Mean	0.0152*	0.0133***	0.0035
CAPM Alpha	0.0162*	0.0141***	0.0040*
FF Alpha	0.0127	0.0106***	0.0041*
CAR Alpha	0.0107	0.0086**	0.0030
Panel 15: Norway			
TS Mean	0.0103	0.0034	0.0015
CAPM Alpha	0.0117	0.0056	0.0036
FF Alpha	0.0084	0.0046	0.0032
CAR Alpha	0.0013	0.0008	0.0028
Panel 16: Italy			
TS Mean	0.0072	0.0013	-0.0019
CAPM Alpha	0.0064	0.0000	-0.0027
FF Alpha	0.0049	-0.0004	-0.0020
CAR Alpha	0.0033	-0.0003	-0.0021
Panel 17: Finland			
TS Mean	0.0091	0.0076	0.0021
CAPM Alpha	0.0091	0.0082*	0.0024
FF Alpha	0.0126	0.0052	-0.0002
CAR Alpha	0.0084	0.0031	-0.0047
Panel 18: Austria			
TS Mean	0.0186	0.0066	-0.0012
CAPM Alpha	0.0221*	0.0079	0.0026
FF Alpha	0.0226*	0.0063	0.0025
CAR Alpha	0.0215*	0.0061	0.0016
Panel 19: Denmark			
TS Mean	-0.0102	0.0012	-0.0057
CAPM Alpha	-0.0096	0.0013	-0.0053
FF Alpha	-0.0109	0.0028	-0.0075
CAR Alpha	-0.0053	0.0017	-0.0096**
Panel 20: Greece			
TS Mean	0.0333**	-0.0092	-0.0076
CAPM Alpha	0.0325**	-0.0084	-0.0065
FF Alpha	0.0327**	-0.0059	-0.0053
CAR Alpha	0.0400**	-0.0071	-0.0070

Table XII. Media Premiums Conditional on Bid-Ask Spreads. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to the bid-ask spread. At the end of each month t we first sort all stocks into terciles according to their bid-ask spread. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage	No-High		
BidAskSpread	Low	Med	High
Panel 1: USA			
TS Mean	0.0036	0.0041*	0.0042
CAPM Alpha	0.0039*	0.0042*	0.0045*
FF Alpha	0.0002	0.0032	0.0048*
CAR Alpha	0.0000	0.0031	0.0046*
Panel 2: Australia			
TS Mean	-0.0021	-0.0001	0.0166
CAPM Alpha	-0.0022	-0.0000	0.0165
FF Alpha	-0.0031	-0.0019	0.0163
CAR Alpha	-0.0026	-0.0004	0.0144
Panel 3: Hongkong			
TS Mean	0.0049	0.0078**	0.0224***
CAPM Alpha	0.0054	0.0088**	0.0231***
FF Alpha	0.0035	0.0077**	0.0243***
CAR Alpha	0.0024	0.0055*	0.0236***
Panel 4: Japan			
TS Mean	0.0003	0.0026*	0.0034**
CAPM Alpha	-0.0001	0.0024*	0.0032**
FF Alpha	-0.0019	0.0022*	0.0029*
CAR Alpha	-0.0020	0.0022*	0.0029*
Panel 5: NewZealand			
TS Mean	-0.0076	0.0011	0.0220
CAPM Alpha	-0.0070	0.0007	0.0256**
FF Alpha	-0.0088	0.0006	0.0238*
CAR Alpha	-0.0083	-0.0029	0.0286**
Panel 6: Singapore			
TS Mean	-0.0021	0.0005	0.0029
CAPM Alpha	-0.0024	0.0003	0.0033
FF Alpha	-0.0014	-0.0001	0.0003
CAR Alpha	-0.0017	0.0000	-0.0016
Panel 7: UK			
TS Mean	0.0008	-0.0003	0.0105**
CAPM Alpha	0.0010	-0.0001	0.0107***
FF Alpha	0.0018	-0.0011	0.0110***
CAR Alpha	0.0023	-0.0013	0.0108***
Panel 8: Germany			
TS Mean	0.0011	0.0061	0.0265***
CAPM Alpha	0.0010	0.0060	0.0264***
FF Alpha	0.0002	0.0014	0.0224***
CAR Alpha	-0.0019	-0.0018	0.0192***
Panel 9: France			
TS Mean	0.0112***	0.0031	0.0135*
CAPM Alpha	0.0107***	0.0026	0.0128**
FF Alpha	0.0096***	0.0021	0.0106*
CAR Alpha	0.0097***	0.0020	0.0098*

Table XII. Media Premiums Conditional on Bid-Ask Spreads - Continued

Media Coverage	No-High		
BidAskSpread	Low	Med	High
Panel 10: Switzerland			
TS Mean	0.0027	0.0083**	0.0090**
CAPM Alpha	0.0023	0.0080**	0.0086**
FF Alpha	0.0023	0.0069**	0.0076**
CAR Alpha	0.0013	0.0063*	0.0063*
Panel 11: Spain			
TS Mean	0.0040	0.0061	0.0069
CAPM Alpha	0.0059	0.0070*	0.0088*
FF Alpha	0.0064	0.0069**	0.0069*
CAR Alpha	0.0062	0.0073*	0.0067
Panel 12: Sweden			
TS Mean	0.0031	0.0069	0.0015
CAPM Alpha	0.0034	0.0070*	0.0017
FF Alpha	0.0044	0.0056	0.0020
CAR Alpha	0.0057*	0.0067	0.0011
Panel 13: Netherlands			
TS Mean	0.0196	0.0137***	0.0070
CAPM Alpha	0.0201*	0.0148***	0.0071
FF Alpha	0.0205	0.0147***	0.0068
CAR Alpha	0.0197*	0.0147***	0.0067
Panel 14: Belgium			
TS Mean	0.0111**	0.0103***	0.0125**
CAPM Alpha	0.0118***	0.0110**	0.0138***
FF Alpha	0.0112***	0.0091***	0.0129***
CAR Alpha	0.0113***	0.0068**	0.0103**
Panel 15: Norway			
TS Mean	0.0019	0.0138**	0.0133
CAPM Alpha	0.0034	0.0154***	0.0151**
FF Alpha	0.0034	0.0147**	0.0146**
CAR Alpha	0.0033	0.0119**	0.0142*
Panel 16: Italy			
TS Mean	-0.0000	0.0034	0.0028
CAPM Alpha	-0.0012	0.0032	0.0022
FF Alpha	-0.0000	0.0045*	0.0013
CAR Alpha	0.0003	0.0056**	0.0000
Panel 17: Finland			
TS Mean	-0.0019	0.0116***	0.0012
CAPM Alpha	-0.0013	0.0117***	0.0019
FF Alpha	-0.0051	0.0111***	0.0029
CAR Alpha	-0.0084**	0.0100**	0.0016
Panel 18: Austria			
TS Mean	-0.0090*	0.0010	0.0278**
CAPM Alpha	-0.0013	0.0067	0.0259**
FF Alpha	-0.0014	0.0063	0.0252**
CAR Alpha	-0.0022	0.0059	0.0257**
Panel 19: Denmark			
TS Mean	0.0007	0.0025	0.0107
CAPM Alpha	0.0012	0.0035	0.0111
FF Alpha	-0.0035	0.0030	0.0105
CAR Alpha	-0.0054	0.0005	0.0096
Panel 20: Greece			
TS Mean	-0.0042	0.0015	0.0122
CAPM Alpha	-0.0037	0.0024	0.0128*
FF Alpha	-0.0021	0.0023	0.0131
CAR Alpha	-0.0005	0.0028	0.0129

Table XIII. Media Premiums Conditional on Amihud's Illiquidity Ratio. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to Amihud's illiquidity ratio. At the end of each month t we first sort all stocks into terciles according to Amihud's illiquidity ratio. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage		No-High	
Amihud	Low	Med	High
Panel 1: USA			
TS Mean	0.0029*	-0.0038*	-0.0015
CAPM Alpha	0.0030**	-0.0036**	-0.0011
FF Alpha	0.0024*	-0.0038**	0.0002
CAR Alpha	0.0024*	-0.0037**	0.0005
Panel 2: Australia			
TS Mean	-0.0055**	0.0033	-0.0165
CAPM Alpha	-0.0055*	0.0033	-0.0167
FF Alpha	-0.0060**	0.0026	-0.0181
CAR Alpha	-0.0041*	0.0041	-0.0137
Panel 3: Hongkong			
TS Mean	-0.0019	0.0104**	0.0191**
CAPM Alpha	-0.0021	0.0114**	0.0211**
FF Alpha	-0.0037*	0.0109*	0.0197**
CAR Alpha	-0.0034*	0.0100*	0.0193**
Panel 4: Japan			
TS Mean	-0.0025	-0.0005	0.0023
CAPM Alpha	-0.0027*	-0.0006	0.0023*
FF Alpha	-0.0036***	-0.0008	0.0028*
CAR Alpha	-0.0036***	-0.0009	0.0028*
Panel 5: NewZealand			
TS Mean	-0.0051	-0.0095**	0.0274**
CAPM Alpha	-0.0051	-0.0091**	0.0295***
FF Alpha	-0.0061	-0.0101**	0.0240**
CAR Alpha	-0.0062	-0.0106**	0.0249**
Panel 6: Singapore			
TS Mean	-0.0100***	-0.0012	0.0018
CAPM Alpha	-0.0117***	-0.0010	0.0025
FF Alpha	-0.0075***	0.0004	-0.0050
CAR Alpha	-0.0066**	0.0021	-0.0098
Panel 7: UK			
TS Mean	-0.0040**	-0.0019	0.0090**
CAPM Alpha	-0.0039*	-0.0019	0.0092**
FF Alpha	-0.0026	-0.0022	0.0079*
CAR Alpha	-0.0016	-0.0018	0.0081*
Panel 8: Germany			
TS Mean	-0.0049*	0.0052	0.0021
CAPM Alpha	-0.0049**	0.0051	0.0017
FF Alpha	-0.0045*	0.0027	-0.0034
CAR Alpha	-0.0052**	0.0004	-0.0013
Panel 9: France			
TS Mean	-0.0000	0.0039	0.0096
CAPM Alpha	-0.0003	0.0036	0.0097
FF Alpha	-0.0008	0.0027	0.0097
CAR Alpha	-0.0005	0.0023	0.0102

Table XIII. Media Premiums Conditional on Amihud's Illiquidity Ratio - Continued

Media Coverage	No-High		
Amihud	Low	Med	High
Panel 10: Switzerland			
TS Mean	0.0034	0.0047	0.0035
CAPM Alpha	0.0031	0.0045	0.0033
FF Alpha	0.0028	0.0031	0.0028
CAR Alpha	0.0027	0.0022	0.0023
Panel 11: Spain			
TS Mean	0.0020	0.0049	0.0088
CAPM Alpha	0.0019	0.0050	0.0074
FF Alpha	0.0037	0.0049	0.0064
CAR Alpha	0.0037	0.0043	0.0040
Panel 12: Sweden			
TS Mean	0.0001	0.0015	0.0060
CAPM Alpha	0.0002	0.0017	0.0060
FF Alpha	0.0017	0.0013	0.0087
CAR Alpha	0.0031	0.0018	0.0101
Panel 13: Netherlands			
TS Mean	0.0062	0.0078**	0.0113*
CAPM Alpha	0.0039	0.0079*	0.0112*
FF Alpha	-0.0004	0.0076*	0.0110*
CAR Alpha	-0.0004	0.0075*	0.0110*
Panel 14: Belgium			
TS Mean	0.0059*	0.0018	0.0161**
CAPM Alpha	0.0063*	0.0024	0.0164**
FF Alpha	0.0043	0.0023	0.0148**
CAR Alpha	0.0043	0.0005	0.0161**
Panel 15: Norway			
TS Mean	0.0016	0.0005	0.0123
CAPM Alpha	0.0024	0.0019	0.0138
FF Alpha	0.0023	0.0003	0.0133
CAR Alpha	0.0043	-0.0038	0.0118
Panel 16: Italy			
TS Mean	-0.0005	0.0022	-0.0125
CAPM Alpha	-0.0013	0.0020	-0.0141
FF Alpha	0.0004	0.0031	-0.0160
CAR Alpha	0.0011	0.0031	-0.0157
Panel 17: Finland			
TS Mean	-0.0026	0.0046	0.0118
CAPM Alpha	-0.0023	0.0041	0.0121*
FF Alpha	-0.0049	0.0078*	0.0142**
CAR Alpha	-0.0080*	0.0082**	0.0108
Panel 18: Austria			
TS Mean	-0.0099**	0.0012	0.0178**
CAPM Alpha	-0.0066**	0.0019	0.0200*
FF Alpha	-0.0063*	0.0031	0.0191*
CAR Alpha	-0.0063*	0.0026	0.0206**
Panel 19: Denmark			
TS Mean	-0.0025	-0.0032	-0.0001
CAPM Alpha	-0.0023	-0.0028	-0.0005
FF Alpha	-0.0054	-0.0019	-0.0001
CAR Alpha	-0.0062	-0.0026	0.0010
Panel 20: Greece			
TS Mean	-0.0123**	0.0009	0.0210
CAPM Alpha	-0.0120**	0.0016	0.0207
FF Alpha	-0.0114**	-0.0005	0.0238
CAR Alpha	-0.0100	0.0030	0.0245

Table XIV. Media Premiums Conditional on Volume. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to trading volume. At the end of each month t we first sort all stocks into terciles according to their trading volume. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage	No-High		
VAavgpastyear	Low	Med	High
Panel 1: USA			
TS Mean	-0.0030	-0.0037**	0.0013
CAPM Alpha	-0.0027	-0.0036**	0.0011
FF Alpha	-0.0017	-0.0031**	0.0017
CAR Alpha	-0.0017	-0.0031**	0.0017
Panel 2: Australia			
TS Mean	0.0016	-0.0058	-0.0064**
CAPM Alpha	0.0018	-0.0058	-0.0065*
FF Alpha	0.0016	-0.0053	-0.0069**
CAR Alpha	0.0037	-0.0050	-0.0058*
Panel 3: Hongkong			
TS Mean	0.0056	0.0025	-0.0042
CAPM Alpha	0.0064	0.0029	-0.0047
FF Alpha	0.0084	0.0033	-0.0066***
CAR Alpha	0.0085	0.0034	-0.0079***
Panel 4: Japan			
TS Mean	-0.0007	-0.0016	-0.0032*
CAPM Alpha	-0.0006	-0.0016	-0.0031
FF Alpha	-0.0004	-0.0011	-0.0038***
CAR Alpha	-0.0004	-0.0011	-0.0038***
Panel 5: NewZealand			
TS Mean	0.0200	0.0008	-0.0094**
CAPM Alpha	0.0195	0.0023	-0.0095**
FF Alpha	0.0136	0.0019	-0.0098**
CAR Alpha	0.0138	0.0024	-0.0111**
Panel 6: Singapore			
TS Mean	0.0038	-0.0013	-0.0103***
CAPM Alpha	0.0037	-0.0028	-0.0123***
FF Alpha	-0.0029	-0.0008	-0.0079**
CAR Alpha	-0.0067	0.0003	-0.0071**
Panel 7: UK			
TS Mean	0.0046	0.0011	-0.0027
CAPM Alpha	0.0048	0.0011	-0.0027
FF Alpha	0.0048	0.0013	-0.0011
CAR Alpha	0.0054	0.0016	0.0002
Panel 8: Germany			
TS Mean	0.0162	0.0047	-0.0051*
CAPM Alpha	0.0157	0.0046	-0.0051**
FF Alpha	0.0102	0.0020	-0.0043**
CAR Alpha	0.0125	-0.0002	-0.0044**
Panel 9: France			
TS Mean	0.0180***	0.0057	0.0004
CAPM Alpha	0.0178***	0.0054*	0.0001
FF Alpha	0.0189***	0.0048	0.0000
CAR Alpha	0.0194***	0.0045	0.0003

Table XIV. Media Premiums Conditional on Volume - Continued

Media Coverage	No-High		
VAavgpastyear	Low	Med	High
Panel 10: Switzerland			
TS Mean	0.0041	0.0054*	0.0029
CAPM Alpha	0.0039	0.0052**	0.0027
FF Alpha	0.0037	0.0041	0.0027
CAR Alpha	0.0025	0.0034	0.0026
Panel 11: Spain			
TS Mean	0.0070	0.0068*	0.0124*
CAPM Alpha	0.0081	0.0067	0.0125
FF Alpha	0.0057	0.0060	0.0141
CAR Alpha	0.0030	0.0050	0.0144*
Panel 12: Sweden			
TS Mean	-0.0006	-0.0032	-0.0002
CAPM Alpha	-0.0006	-0.0029	-0.0002
FF Alpha	-0.0001	-0.0036	0.0022
CAR Alpha	0.0013	-0.0029	0.0023
Panel 13: Netherlands			
TS Mean	0.0113	0.0076*	0.0116
CAPM Alpha	0.0110	0.0080**	0.0097
FF Alpha	0.0104	0.0081**	-0.0001
CAR Alpha	0.0102	0.0081**	-0.0007
Panel 14: Belgium			
TS Mean	0.0142	0.0088***	0.0037
CAPM Alpha	0.0143*	0.0093***	0.0041
FF Alpha	0.0123	0.0085***	0.0024
CAR Alpha	0.0145*	0.0071**	0.0020
Panel 15: Norway			
TS Mean	0.0070	0.0023	-0.0014
CAPM Alpha	0.0091	0.0029	-0.0009
FF Alpha	0.0060	0.0030	-0.0009
CAR Alpha	-0.0021	0.0006	-0.0006
Panel 16: Italy			
TS Mean	-0.0014	0.0030	-0.0027
CAPM Alpha	-0.0017	0.0031	-0.0029
FF Alpha	-0.0024	0.0042	-0.0003
CAR Alpha	-0.0033	0.0039	0.0006
Panel 17: Finland			
TS Mean	0.0116	0.0029	-0.0023
CAPM Alpha	0.0117	0.0025	-0.0021
FF Alpha	0.0140*	0.0060	-0.0039
CAR Alpha	0.0072	0.0054	-0.0079*
Panel 18: Austria			
TS Mean	0.0211***	0.0121	-0.0100**
CAPM Alpha	0.0190**	0.0136*	-0.0072*
FF Alpha	0.0197**	0.0149*	-0.0070*
CAR Alpha	0.0195**	0.0152*	-0.0072*
Panel 19: Denmark			
TS Mean	-0.0080	0.0052	-0.0032
CAPM Alpha	-0.0083	0.0055	-0.0030
FF Alpha	-0.0067	0.0062	-0.0057
CAR Alpha	-0.0041	0.0060	-0.0061
Panel 20: Greece			
TS Mean	0.0042	0.0020	-0.0149**
CAPM Alpha	0.0042	0.0022	-0.0144***
FF Alpha	0.0123	-0.0023	-0.0141**
CAR Alpha	0.0099	0.0004	-0.0133**

Table XV. Media Premiums Conditional on Price. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to Price. At the end of each month t we first sort all stocks into terciles according to their price. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage	No-High		
Pusd	Low	Med	High
Panel 1: USA			
TS Mean	-0.0020	-0.0055**	-0.0014
CAPM Alpha	-0.0015	-0.0050**	-0.0013
FF Alpha	-0.0008	-0.0061**	-0.0031**
CAR Alpha	-0.0011	-0.0063***	-0.0031**
Panel 2: Australia			
TS Mean	0.0221**	-0.0025	-0.0105***
CAPM Alpha	0.0217**	-0.0026	-0.0105***
FF Alpha	0.0211**	-0.0043	-0.0119***
CAR Alpha	0.0240***	-0.0060	-0.0111***
Panel 3: Hongkong			
TS Mean	0.0098	0.0017	-0.0031
CAPM Alpha	0.0106	0.0036	-0.0015
FF Alpha	0.0103	0.0044	-0.0029
CAR Alpha	0.0086	0.0021	-0.0051***
Panel 4: Japan			
TS Mean	0.0023	-0.0026*	0.0008
CAPM Alpha	0.0020	-0.0031**	0.0006
FF Alpha	0.0035**	-0.0021*	-0.0012
CAR Alpha	0.0036***	-0.0020*	-0.0012
Panel 5: NewZealand			
TS Mean	0.0168	-0.0137*	-0.0022
CAPM Alpha	0.0183*	-0.0130*	-0.0015
FF Alpha	0.0186	-0.0149	-0.0016
CAR Alpha	0.0156	-0.0129	-0.0035
Panel 6: Singapore			
TS Mean	0.0128**	-0.0099**	-0.0052**
CAPM Alpha	0.0141**	-0.0085**	-0.0044**
FF Alpha	0.0115*	-0.0095*	-0.0040*
CAR Alpha	0.0068	-0.0089*	-0.0039*
Panel 7: UK			
TS Mean	-0.0017	-0.0061**	-0.0038*
CAPM Alpha	-0.0014	-0.0059**	-0.0036
FF Alpha	-0.0007	-0.0057*	-0.0025
CAR Alpha	-0.0020	-0.0065**	-0.0018
Panel 8: Germany			
TS Mean	0.0214***	0.0002	0.0044
CAPM Alpha	0.0213***	0.0000	0.0043
FF Alpha	0.0169***	-0.0011	0.0022
CAR Alpha	0.0145**	-0.0047	-0.0000
Panel 9: France			
TS Mean	0.0132**	-0.0007	0.0053
CAPM Alpha	0.0124**	-0.0014	0.0046**
FF Alpha	0.0117**	-0.0022	0.0027*
CAR Alpha	0.0101**	-0.0026	0.0030*

Table XV. Media Premiums Conditional on Price - Continued

Media Coverage	No-High		
Pusd	Low	Med	High
Panel 10: Switzerland			
TS Mean	0.0046	0.0037	0.0056**
CAPM Alpha	0.0041	0.0033	0.0053**
FF Alpha	0.0038	0.0036	0.0049**
CAR Alpha	0.0035	0.0033	0.0040*
Panel 11: Spain			
TS Mean	0.0068	0.0026	0.0050
CAPM Alpha	0.0074*	0.0037	0.0057*
FF Alpha	0.0070**	0.0049	0.0054*
CAR Alpha	0.0060*	0.0037	0.0054*
Panel 12: Sweden			
TS Mean	0.0114*	-0.0098**	-0.0043
CAPM Alpha	0.0118**	-0.0095***	-0.0041
FF Alpha	0.0116*	-0.0095***	-0.0012
CAR Alpha	0.0114*	-0.0102***	-0.0011
Panel 13: Netherlands			
TS Mean	0.0087	0.0093**	0.0051
CAPM Alpha	0.0082	0.0093**	0.0060**
FF Alpha	0.0086*	0.0084**	0.0049*
CAR Alpha	0.0084*	0.0083**	0.0049*
Panel 14: Belgium			
TS Mean	0.0173***	0.0008	0.0119***
CAPM Alpha	0.0183***	0.0016	0.0132***
FF Alpha	0.0200***	0.0012	0.0090***
CAR Alpha	0.0182***	0.0003	0.0087***
Panel 15: Norway			
TS Mean	0.0070	0.0004	-0.0019
CAPM Alpha	0.0092	0.0016	0.0022
FF Alpha	0.0083	0.0016	0.0012
CAR Alpha	0.0038	0.0003	0.0017
Panel 16: Italy			
TS Mean	-0.0007	-0.0011	-0.0037
CAPM Alpha	-0.0010	-0.0022	-0.0051*
FF Alpha	-0.0011	-0.0006	-0.0032
CAR Alpha	-0.0014	-0.0004	-0.0026
Panel 17: Finland			
TS Mean	0.0031	0.0043	0.0044
CAPM Alpha	0.0037	0.0049	0.0050
FF Alpha	0.0046	0.0030	0.0037
CAR Alpha	0.0030	0.0018	0.0001
Panel 18: Austria			
TS Mean	0.0063	-0.0025	0.0077
CAPM Alpha	0.0094	0.0013	0.0114**
FF Alpha	0.0101	0.0005	0.0110**
CAR Alpha	0.0079	0.0008	0.0113**
Panel 19: Denmark			
TS Mean	-0.0011	-0.0030	-0.0032
CAPM Alpha	-0.0004	-0.0018	-0.0025
FF Alpha	0.0015	-0.0043	-0.0068
CAR Alpha	-0.0006	-0.0063	-0.0085*
Panel 20: Greece			
TS Mean	0.0065	-0.0070	-0.0119**
CAPM Alpha	0.0081	-0.0053	-0.0107**
FF Alpha	0.0112	-0.0018	-0.0092*
CAR Alpha	0.0031	-0.0045	-0.0093

Table XVI. Media Premiums Conditional on Past Year Return. This table reports the profitability of equally weighted No minus High media coverage (No-High) portfolio returns for subgroups of stocks sorted according to Past Year Return. At the end of each month t we first sort all stocks into terciles according to their return over the past year. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The portfolios are held during month $t+1$ and rebalanced monthly. Time-series means plus alpha estimates from regressing the monthly returns on the No-High portfolio on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Media Coverage	No-High		
RETpastyear	Low	Med	High
Panel 1: USA			
TS Mean	0.0018	0.0027	0.0101***
CAPM Alpha	0.0023	0.0029	0.0103***
FF Alpha	0.0005	0.0009	0.0094***
CAR Alpha	0.0002	0.0008	0.0095***
Panel 2: Australia			
TS Mean	0.0151***	0.0046	0.0054
CAPM Alpha	0.0149***	0.0045	0.0054
FF Alpha	0.0128***	0.0026	0.0037
CAR Alpha	0.0109**	0.0031	0.0052
Panel 3: Hongkong			
TS Mean	0.0135***	0.0080*	0.0143***
CAPM Alpha	0.0151***	0.0096*	0.0151***
FF Alpha	0.0136***	0.0082**	0.0115***
CAR Alpha	0.0111***	0.0050	0.0110***
Panel 4: Japan			
TS Mean	0.0030	0.0010	0.0041***
CAPM Alpha	0.0027	0.0007	0.0039**
FF Alpha	0.0018	0.0003	0.0030**
CAR Alpha	0.0020	0.0004	0.0029**
Panel 5: NewZealand			
TS Mean	0.0037	-0.0102*	0.0065*
CAPM Alpha	0.0027	-0.0090	0.0074**
FF Alpha	0.0012	-0.0103	0.0076*
CAR Alpha	0.0029	-0.0107	0.0092**
Panel 6: Singapore			
TS Mean	-0.0052	0.0002	0.0044
CAPM Alpha	-0.0050	0.0000	0.0046
FF Alpha	-0.0063	-0.0000	0.0041
CAR Alpha	-0.0051	-0.0004	0.0037
Panel 7: UK			
TS Mean	-0.0039	-0.0043*	0.0034*
CAPM Alpha	-0.0035	-0.0040**	0.0036*
FF Alpha	-0.0021	-0.0030*	0.0036**
CAR Alpha	-0.0026	-0.0026*	0.0049***
Panel 8: Germany			
TS Mean	0.0190***	0.0049	0.0056
CAPM Alpha	0.0189***	0.0048	0.0056*
FF Alpha	0.0167***	0.0039	0.0037
CAR Alpha	0.0141***	0.0017	0.0030
Panel 9: France			
TS Mean	0.0076*	0.0028	0.0101***
CAPM Alpha	0.0068**	0.0023	0.0098***
FF Alpha	0.0057**	0.0015	0.0087***
CAR Alpha	0.0052*	0.0015	0.0093***

Table XVI. Media Premiums Conditional on Past Year Return - Continued

Media Coverage	No-High		
RETpastyear	Low	Med	High
Panel 10: Switzerland			
TS Mean	0.0013	0.0046	0.0071***
CAPM Alpha	0.0009	0.0042	0.0069***
FF Alpha	0.0006	0.0043*	0.0068***
CAR Alpha	0.0002	0.0041	0.0069***
Panel 11: Spain			
TS Mean	0.0041	-0.0004	0.0100***
CAPM Alpha	0.0053	-0.0001	0.0115***
FF Alpha	0.0049	0.0013	0.0123***
CAR Alpha	0.0038	0.0010	0.0122***
Panel 12: Sweden			
TS Mean	0.0022	0.0041	-0.0020
CAPM Alpha	0.0027	0.0042	-0.0018
FF Alpha	0.0056	0.0068*	-0.0018
CAR Alpha	0.0029	0.0071**	0.0012
Panel 13: Netherlands			
TS Mean	-0.0034	0.0091**	0.0120**
CAPM Alpha	-0.0041	0.0096***	0.0126***
FF Alpha	-0.0052	0.0091***	0.0128***
CAR Alpha	-0.0054	0.0091***	0.0130***
Panel 14: Belgium			
TS Mean	0.0075	0.0026	0.0091***
CAPM Alpha	0.0089**	0.0033	0.0097***
FF Alpha	0.0092**	0.0016	0.0088***
CAR Alpha	0.0072*	0.0022	0.0071**
Panel 15: Norway			
TS Mean	0.0092	0.0026	0.0004
CAPM Alpha	0.0106	0.0049	0.0027
FF Alpha	0.0101	0.0042	0.0023
CAR Alpha	0.0074	0.0037	0.0028
Panel 16: Italy			
TS Mean	0.0064	-0.0009	-0.0008
CAPM Alpha	0.0058	-0.0017	-0.0019
FF Alpha	0.0089**	-0.0010	-0.0020
CAR Alpha	0.0088**	-0.0012	-0.0009
Panel 17: Finland			
TS Mean	0.0068	0.0079*	0.0046
CAPM Alpha	0.0072	0.0086**	0.0052
FF Alpha	0.0063	0.0074**	0.0058
CAR Alpha	0.0060	0.0064	0.0031
Panel 18: Austria			
TS Mean	0.0106	0.0012	0.0061
CAPM Alpha	0.0116**	0.0037	0.0108**
FF Alpha	0.0127**	0.0025	0.0104**
CAR Alpha	0.0120**	0.0026	0.0111***
Panel 19: Denmark			
TS Mean	0.0040	-0.0018	-0.0067
CAPM Alpha	0.0046	-0.0008	-0.0060
FF Alpha	0.0046	-0.0023	-0.0081*
CAR Alpha	0.0004	-0.0055*	-0.0080*
Panel 20: Greece			
TS Mean	0.0087	0.0008	-0.0055
CAPM Alpha	0.0095	0.0014	-0.0047
FF Alpha	0.0117	0.0037	-0.0028
CAR Alpha	0.0121	0.0058	-0.0020

A.5 Media Effect and Market States: Double-Sort Results

Table XVII. Conditional Strategy Returns in the U.S. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t + 1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
	Panel 1: By MVyearlyavg		
1	0.0071*	0.0064*	0.0061*
2	0.0021	0.0016	0.0014
3	-0.0014	-0.0011	-0.0013
	Panel 2: By MTBVyearly		
1	0.0051**	0.0056**	0.0055**
2	0.0015	0.0017	0.0016
3	0.0072***	0.0070***	0.0070***
	Panel 3: By RETpastyear		
1	0.0086***	0.0091***	0.0091***
2	0.0063***	0.0067***	0.0067***
3	0.0051***	0.0045***	0.0045***
	Panel 4: By RETcurrentmonth		
1	0.0074***	0.0075***	0.0075***
2	0.0059***	0.0060***	0.0059***
3	0.0072***	0.0067***	0.0065**
	Panel 5: By Pavgpast		
1	0.0070***	0.0075***	0.0071***
2	0.0022	0.0023	0.0022
3	-0.0012	-0.0017	-0.0018
	Panel 6: By BidAskSpread		
1	0.0046**	0.0042**	0.0041**
2	0.0040*	0.0039**	0.0039**
3	0.0054**	0.0057**	0.0056**
	Panel 7: By VAavgpastyear		
1	-0.0003	0.0002	0.0002
2	0.0018	0.0017	0.0017
3	-0.0030	-0.0029	-0.0027
	Panel 8: By Amihud		
1	-0.0018	-0.0019	-0.0020
2	0.0032*	0.0029*	0.0027*
3	0.0045	0.0040	0.0038

Table XVIII. Conditional Strategy Returns in Australia. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: By MVyearlyavg			
1	0.0098	0.0099	0.0103
2	0.0068	0.0069	0.0058
3	0.0080***	0.0079***	0.0079***
Panel 2: By MTBVyearly			
1	0.0113***	0.0114***	0.0119***
2	0.0128***	0.0132***	0.0138***
3	0.0087**	0.0087**	0.0088**
Panel 3: By RETpastyear			
1	0.0185***	0.0188***	0.0197***
2	0.0118***	0.0122***	0.0132***
3	0.0095***	0.0095***	0.0097***
Panel 4: By RETcurrentmonth			
1	0.0082	0.0079*	0.0096**
2	0.0126***	0.0129***	0.0131***
3	0.0157***	0.0162***	0.0166***
Panel 5: By Pavgpast			
1	0.0486**	0.0478**	0.0534**
2	0.0009	0.0013	0.0008
3	0.0081***	0.0081***	0.0083***
Panel 6: By BidAskSpread			
1	0.0074***	0.0073***	0.0075***
2	0.0073	0.0077	0.0086
3	0.0158	0.0143	0.0163
Panel 7: By VAavgpastyear			
1	0.0048	0.0039	0.0040
2	0.0101	0.0081	0.0095
3	0.0088***	0.0083***	0.0081**
Panel 8: By Amihud			
1	0.0086***	0.0083***	0.0085***
2	0.0012	0.0005	0.0016
3	0.0280*	0.0278*	0.0287*

Table XIX. Conditional Strategy Returns in Hongkong. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: By MVyearlyavg			
1	-0.0017	-0.0007	-0.0017
2	-0.0011	-0.0019	-0.0034
3	0.0047*	0.0058**	0.0054**
Panel 2: By MTBVyearly			
1	0.0011	-0.0019	-0.0023
2	0.0064	0.0075**	0.0056*
3	0.0111***	0.0112***	0.0128***
Panel 3: By RETpastyear			
1	0.0056	0.0055	0.0064
2	0.0141**	0.0145***	0.0137***
3	0.0100**	0.0093***	0.0087***
Panel 4: By RETcurrentmonth			
1	0.0080*	0.0086**	0.0077***
2	0.0109***	0.0099***	0.0107***
3	0.0128**	0.0114**	0.0108**
Panel 5: By Pavgpast			
1	-0.0010	0.0034	0.0033
2	-0.0000	-0.0009	-0.0021
3	0.0034	0.0041*	0.0038*
Panel 6: By BidAskSpread			
1	0.0134***	0.0135***	0.0125***
2	0.0048	0.0051	0.0054
3	-0.0070	-0.0082	-0.0089
Panel 7: By VAavgpastyear			
1	0.0033	0.0051	0.0051
2	0.0049	0.0025	0.0023
3	0.0113***	0.0124***	0.0118***
Panel 8: By Amihud			
1	0.0083***	0.0091***	0.0083***
2	0.0022	0.0003	-0.0007
3	0.0036	0.0046	0.0032

Table XX. Conditional Strategy Returns in Japan. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
	Panel 1: By MVyearlyavg		
1	0.0019	0.0027*	0.0026*
2	0.0006	0.0009	0.0009
3	0.0001	0.0012	0.0013
	Panel 2: By MTBVyearly		
1	0.0014	-0.0012	-0.0015
2	0.0034	0.0043	0.0045
3	0.0028	0.0036	0.0039
	Panel 3: By RETpastyear		
1	0.0013	0.0018	0.0018
2	0.0026**	0.0028**	0.0028**
3	0.0042***	0.0053***	0.0054***
	Panel 4: By RETcurrentmonth		
1	0.0023*	0.0040***	0.0041***
2	0.0025**	0.0030**	0.0031***
3	0.0028*	0.0028	0.0029*
	Panel 5: By Pavgpast		
1	0.0037**	0.0036**	0.0036**
2	0.0027*	0.0031**	0.0030**
3	0.0036*	0.0042**	0.0043**
	Panel 6: By BidAskSpread		
1	0.0020	0.0031**	0.0031**
2	0.0017	0.0023	0.0024*
3	0.0033**	0.0042**	0.0043**
	Panel 7: By VAavgpastyear		
1	0.0016	0.0021*	0.0021*
2	0.0004	0.0007	0.0007
3	0.0016	0.0020	0.0022
	Panel 8: By Amihud		
1	0.0010	0.0019	0.0021
2	0.0002	0.0003	0.0003
3	0.0023*	0.0031**	0.0031**

Table XXI. Conditional Strategy Returns in New Zealand. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
	Panel 1: By MVyearlyavg		
1	0.0025	-0.0011	0.0052
2	0.0029	0.0037	0.0021
3	0.0056	0.0070	0.0067
	Panel 2: By MTBVyearly		
1	0.0339	0.0414	0.0446
2	0.0079*	0.0071*	0.0072*
3	-0.0002	0.0008	-0.0010
	Panel 3: By RETpastyear		
1	0.0148**	0.0131*	0.0094
2	0.0099*	0.0119*	0.0126*
3	-0.0025	-0.0030	-0.0030
	Panel 4: By RETcurrentmonth		
1	0.0069	0.0058	0.0057
2	0.0130	0.0186**	0.0194**
3	0.0085*	0.0088**	0.0085*
	Panel 5: By Pavgpast		
1	0.0101	0.0068	0.0088
2	0.0123	0.0152	0.0153
3	0.0022	0.0029	0.0024
	Panel 6: By BidAskSpread		
1	0.0089*	0.0099*	0.0090
2	0.0042	0.0031	0.0033
3	0.0015	0.0018	-0.0093
	Panel 7: By VAavgpastyear		
1	0.0117	0.0107	0.0113
2	0.0025	0.0030	0.0014
3	0.0089*	0.0095*	0.0100
	Panel 8: By Amihud		
1	0.0067	0.0072	0.0067
2	0.0032	0.0037	0.0039
3	0.0004	-0.0034	-0.0052

Table XXII. Conditional Strategy Returns in Singapore. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: By MVyearlyavg			
1	-0.0098	-0.0124	-0.0123
2	-0.0009	0.0018	0.0019
3	-0.0041**	0.0032	0.0037*
Panel 2: By MTBVyearly			
1	-0.0035	-0.0013	-0.0010
2	0.0174***	0.0136***	0.0147***
3	0.0096	0.0057	0.0063
Panel 3: By RETpastyear			
1	0.0063	0.0099**	0.0094**
2	0.0022	0.0008	0.0014
3	0.0014	0.0009	0.0014
Panel 4: By RETcurrentmonth			
1	0.0012	0.0014	0.0021
2	0.0043	0.0038	0.0040
3	0.0074**	0.0070**	0.0067**
Panel 5: By Pavgpast			
1	0.0016	0.0007	0.0030
2	-0.0048	-0.0055	-0.0055
3	-0.0001	0.0002	0.0004
Panel 6: By BidAskSpread			
1	0.0026	0.0015	0.0024
2	0.0061*	0.0050	0.0063
3	-0.0002	0.0009	0.0018
Panel 7: By VAavgpastyear			
1	0.0064	0.0142	0.0159
2	0.0012	0.0020	0.0019
3	0.0063**	0.0018	0.0027
Panel 8: By Amihud			
1	0.0072***	0.0035	0.0045
2	-0.0054	-0.0044	-0.0068
3	0.0064	0.0067	0.0107

Table XXIII. Conditional Strategy Returns in the UK. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
	Panel 1: By MVyearlyavg		
1	-0.0076*	-0.0074	-0.0071
2	0.0048*	0.0056**	0.0057**
3	0.0047**	0.0045**	0.0041*
	Panel 2: By MTBVyearly		
1	0.0092***	0.0078***	0.0084***
2	0.0078***	0.0073***	0.0073***
3	0.0112***	0.0109***	0.0112***
	Panel 3: By RETpastyear		
1	0.0077*	0.0068*	0.0078*
2	0.0078***	0.0076***	0.0078***
3	0.0017	0.0024	0.0021
	Panel 4: By RETcurrentmonth		
1	0.0049	0.0038	0.0043
2	0.0129***	0.0133***	0.0138***
3	0.0060**	0.0063**	0.0058**
	Panel 5: By Pavgpast		
1	-0.0006	-0.0002	0.0006
2	0.0041	0.0034	0.0049
3	0.0049**	0.0049**	0.0052**
	Panel 6: By BidAskSpread		
1	0.0050**	0.0050**	0.0054**
2	0.0028	0.0034	0.0038
3	-0.0030	-0.0029	-0.0020
	Panel 7: By VAavgpastyear		
1	-0.0053	-0.0050	-0.0045
2	0.0021	0.0021	0.0017
3	0.0066***	0.0061***	0.0060***
	Panel 8: By Amihud		
1	0.0055***	0.0052**	0.0052**
2	0.0037	0.0038	0.0032
3	-0.0115***	-0.0107***	-0.0104**

Table XXIV. Conditional Strategy Returns in Germany. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t + 1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: By MVyearlyavg			
1	0.0200*	0.0227*	0.0231*
2	-0.0037	-0.0005	0.0001
3	0.0013	0.0036	0.0057*
Panel 2: By MTBVyearly			
1	0.0091	0.0128	0.0152*
2	0.0010	0.0022	0.0050*
3	-0.0006	0.0028	0.0050
Panel 3: By RETpastyear			
1	0.0036	0.0068	0.0099*
2	-0.0010	0.0006	0.0028
3	-0.0002	0.0014	0.0026
Panel 4: By RETcurrentmonth			
1	-0.0074	-0.0049	-0.0023
2	0.0012	0.0035	0.0052*
3	0.0074**	0.0092**	0.0106**
Panel 5: By Pavgpast			
1	0.0049	0.0077	0.0091
2	0.0001	0.0016	0.0045
3	-0.0004	0.0029	0.0050
Panel 6: By BidAskSpread			
1	0.0001	0.0021	0.0046
2	0.0028	0.0059	0.0080
3	-0.0069	-0.0035	-0.0017
Panel 7: By VAavgpastyear			
1	0.0064	0.0102	0.0069
2	0.0012	0.0021	0.0027
3	0.0068**	0.0077**	0.0097***
Panel 8: By Amihud			
1	0.0054*	0.0070**	0.0089***
2	0.0001	0.0010	0.0011
3	0.0158	0.0196	0.0156

Table XXV. Conditional Strategy Returns in France. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t + 1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
	Panel 1: By MVyearlyavg		
1	-0.0049	-0.0044	-0.0051
2	-0.0024	-0.0028	-0.0025
3	0.0068***	0.0072***	0.0074***
	Panel 2: By MTBVyearly		
1	0.0036	0.0049	0.0049
2	0.0083***	0.0088***	0.0086***
3	0.0076**	0.0081***	0.0080***
	Panel 3: By RETpastyear		
1	0.0103***	0.0113***	0.0113***
2	0.0065***	0.0068***	0.0067***
3	0.0061***	0.0062***	0.0061***
	Panel 4: By RETcurrentmonth		
1	0.0048	0.0056*	0.0053*
2	0.0066***	0.0070***	0.0071***
3	0.0084***	0.0084***	0.0084***
	Panel 5: By Pavgpast		
1	0.0050	0.0062	0.0057
2	0.0078***	0.0082***	0.0085***
3	0.0055**	0.0060**	0.0060**
	Panel 6: By BidAskSpread		
1	0.0115***	0.0121***	0.0122***
2	0.0038*	0.0036	0.0036
3	-0.0072	-0.0073	-0.0068
	Panel 7: By VAavgpastyear		
1	0.0057	0.0063	0.0064
2	-0.0012	-0.0005	-0.0005
3	0.0087***	0.0090***	0.0091***
	Panel 8: By Amihud		
1	0.0093***	0.0096***	0.0097***
2	-0.0021	-0.0020	-0.0021
3	-0.0028	-0.0041	-0.0045

Table XXVI. Conditional Strategy Returns in Switzerland. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: By MVyearlyavg			
1	0.0030	0.0024	0.0035
2	-0.0028	-0.0021	-0.0011
3	0.0049*	0.0058**	0.0065**
Panel 2: By MTBVyearly			
1	0.0019	0.0022	0.0030
2	0.0006	0.0006	0.0023
3	0.0089***	0.0090***	0.0096***
Panel 3: By RETpastyear			
1	0.0062*	0.0057	0.0075**
2	0.0076***	0.0075***	0.0081***
3	0.0017	0.0022	0.0031
Panel 4: By RETcurrentmonth			
1	0.0061*	0.0070**	0.0083**
2	0.0054*	0.0047*	0.0056**
3	0.0064**	0.0067**	0.0078***
Panel 5: By Pavgpast			
1	0.0097***	0.0105***	0.0123***
2	0.0071***	0.0069***	0.0081***
3	0.0009	0.0003	0.0009
Panel 6: By BidAskSpread			
1	0.0065**	0.0067**	0.0079**
2	0.0035	0.0044	0.0057**
3	-0.0015	-0.0004	0.0004
Panel 7: By VAavgpastyear			
1	-0.0021	-0.0020	-0.0020
2	0.0007	0.0021	0.0026
3	0.0031	0.0044	0.0051*
Panel 8: By Amihud			
1	0.0035	0.0043*	0.0050**
2	-0.0006	0.0015	0.0021
3	-0.0033	-0.0033	-0.0023

Table XXVII. Conditional Strategy Returns in Spain. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
Panel 1: By MVyearlyavg			
1	-0.0065	-0.0059	-0.0051
2	-0.0032	-0.0036	-0.0031
3	0.0049	0.0037	0.0040
Panel 2: By MTBVyearly			
1	-0.0027	-0.0042	-0.0033
2	0.0028	0.0029	0.0026
3	0.0102***	0.0102***	0.0100***
Panel 3: By RETpastyear			
1	-0.0009	-0.0003	-0.0008
2	0.0045	0.0044	0.0048
3	0.0015	0.0014	0.0019
Panel 4: By RETcurrentmonth			
1	0.0064**	0.0056*	0.0061*
2	-0.0011	-0.0013	-0.0018
3	0.0041	0.0042	0.0043
Panel 5: By Pavgpast			
1	0.0011	0.0007	0.0008
2	0.0032	0.0027	0.0030
3	0.0021	0.0020	0.0021
Panel 6: By BidAskSpread			
1	0.0081**	0.0064**	0.0064*
2	0.0017	0.0018	0.0019
3	-0.0072	-0.0063	-0.0069
Panel 7: By VAavgpastyear			
1	-0.0101*	-0.0100*	-0.0086
2	-0.0032	-0.0025	-0.0018
3	0.0011	-0.0009	-0.0015
Panel 8: By Amihud			
1	-0.0001	-0.0027	-0.0026
2	-0.0063	-0.0055	-0.0053
3	-0.0120	-0.0108	-0.0119

Table XXVIII. Conditional Strategy Returns in Sweden. This table reports the profitability of equally weighted portfolio returns for subgroups of stocks. At the end of each month t we first sort all stocks into terciles according to firm characteristics. Within each of the resulting terciles, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the percentage of stocks with positive (negative) returns during that month exceeds 50%. Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t+1$ and rebalanced monthly. Alpha estimates from regressing the resulting monthly returns on widely accepted risk factors are presented. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Tercile	CAPM Alpha	FF Alpha	Carhart Alpha
	Panel 1: By MVyearlyavg		
1	0.0079	0.0057	0.0058
2	-0.0016	-0.0013	-0.0009
3	0.0052*	0.0055*	0.0050*
	Panel 2: By MTBVyearly		
1	0.0000	0.0009	0.0010
2	0.0115**	0.0117**	0.0113*
3	0.0066	0.0056	0.0075*
	Panel 3: By RETpastyear		
1	0.0103*	0.0101	0.0102
2	0.0098***	0.0094**	0.0085*
3	0.0039	0.0029	0.0042
	Panel 4: By RETcurrentmonth		
1	-0.0051	-0.0048	-0.0040
2	0.0094***	0.0096***	0.0088**
3	0.0140***	0.0136**	0.0130**
	Panel 5: By Pavgpast		
1	0.0105	0.0117	0.0116
2	0.0068	0.0069	0.0056
3	0.0025	0.0018	0.0025
	Panel 6: By BidAskSpread		
1	0.0027	0.0012	0.0013
2	-0.0000	0.0009	0.0021
3	0.0045	0.0034	0.0045
	Panel 7: By VAavgpastyear		
1	0.0036	0.0021	0.0029
2	0.0026	0.0042	0.0051
3	0.0039	0.0045	0.0041
	Panel 8: By Amihud		
1	0.0063*	0.0064*	0.0068*
2	-0.0022	-0.0009	-0.0010
3	0.0055	0.0026	0.0037

B Internet Appendix

B.1 Using Equal-Weighted Market Returns to proxy the Market State

Table XXIX. Market State Based Media Strategy Returns Across Countries. At the end of each month t, we form three portfolios based on media coverage. The No portfolio consists of stocks that have no media coverage during month t. Covered stocks are divided into two portfolios: Low (High) contains the stocks with media coverage lower (higher) than the median media coverage in month t. The market state in a given month is considered good/bullish (bad/bearish), if the equal-weighted market return during that month is positive (negative). Following good (bad) market state months, we go long (short) the No-Coverage and short (long) the High-Coverage portfolio. The portfolios are held during month $t + 1$ and rebalanced monthly. The resulting returns are evaluated against widely accepted risk factors. Time-series means and factor alphas are reported. 2-sided p-values from Newey-West standard errors using 6 lags are represented by * signs. * denotes 10%, ** denotes 5% and *** denotes 1% significance levels.

Regression Model	Long Leg	Short Leg	Long-Short
Panel 1: USA			
TS Mean	0.0147	0.0081	0.0065***
CAPM Alpha	0.0116***	0.0052**	0.0065***
FF Alpha	0.0082***	0.0019	0.0063***
Carhart Alpha	0.0084***	0.0021	0.0063***
Panel 2: Australia			
TS Mean	0.0237	0.0069	0.0169***
CAPM Alpha	0.0213	0.0044	0.0169***
FF Alpha	0.0262***	0.0099	0.0163***
Carhart Alpha	0.0349***	0.0189***	0.0159***
Panel 3: Hongkong			
TS Mean	0.0195	0.0054	0.0142***
CAPM Alpha	0.0098*	-0.0044	0.0141***
FF Alpha	0.0037**	-0.0088***	0.0126***
Carhart Alpha	0.0035**	-0.0071***	0.0106***
Panel 4: Japan			
TS Mean	0.0072	0.0037	0.0035***
CAPM Alpha	0.0077***	0.0042*	0.0035***
FF Alpha	0.0040***	0.0002	0.0039***
Carhart Alpha	0.0039***	0.0000	0.0039***
Panel 5: NewZealand			
TS Mean	0.0188	0.0095	0.0093**
CAPM Alpha	0.0110**	0.0017	0.0093**
FF Alpha	0.0127**	0.0019	0.0108**
Carhart Alpha	0.0136**	0.0022	0.0114**
Panel 6: Singapore			
TS Mean	0.0143	0.0083	0.0060**
CAPM Alpha	0.0051**	-0.0001	0.0052**
FF Alpha	0.0017	-0.0005	0.0021
Carhart Alpha	0.0024	-0.0002	0.0027
Panel 7: UK			
TS Mean	0.0058	-0.0009	0.0067***
CAPM Alpha	0.0023	-0.0044	0.0067***
FF Alpha	0.0091	0.0027	0.0065***
Carhart Alpha	0.0147***	0.0084	0.0063***
Panel 8: Germany			
TS Mean	0.0061	0.0051	0.0010
CAPM Alpha	0.0051	0.0041	0.0010
FF Alpha	0.0106	0.0111	-0.0004
Carhart Alpha	0.0193***	0.0194***	-0.0001
Panel 9: France			
TS Mean	0.0139	0.0050	0.0089***
CAPM Alpha	0.0135*	0.0046	0.0089***
FF Alpha	0.0194***	0.0100*	0.0094***
Carhart Alpha	0.0210***	0.0117**	0.0093***

Table XXIX. Market State Based Media Strategy Returns Across Countries - Continued

Regression Model	Long Leg	Short Leg	Long-Short
Panel 10: Switzerland			
TS Mean	0.0076	0.0060	0.0016
CAPM Alpha	0.0093	0.0077	0.0015
FF Alpha	0.0109*	0.0089	0.0021
Carhart Alpha	0.0143***	0.0120***	0.0024
Panel 11: Spain			
TS Mean	0.0100	0.0022	0.0078**
CAPM Alpha	0.0052	-0.0019	0.0071***
FF Alpha	0.0046*	-0.0022	0.0067***
Carhart Alpha	0.0064**	-0.0005	0.0069***
Panel 12: Sweden			
TS Mean	0.0089	0.0049	0.0040
CAPM Alpha	0.0072	0.0033	0.0039
FF Alpha	0.0110	0.0061	0.0050
Carhart Alpha	0.0151*	0.0106	0.0044
Panel 13: Netherlands			
TS Mean	0.0081	0.0063	0.0018
CAPM Alpha	0.0045	0.0022	0.0023
FF Alpha	0.0042	0.0021	0.0020
Carhart Alpha	0.0041	0.0021	0.0020
Panel 14: Belgium			
TS Mean	0.0086	0.0087	-0.0001
CAPM Alpha	0.0047*	0.0048**	-0.0000
FF Alpha	0.0021	0.0021	0.0000
Carhart Alpha	0.0016	0.0028	-0.0012
Panel 15: Norway			
TS Mean	0.0082	0.0098	-0.0017
CAPM Alpha	-0.0037	-0.0011	-0.0025
FF Alpha	-0.0043	-0.0013	-0.0030
Carhart Alpha	-0.0023	0.0003	-0.0026
Panel 16: Italy			
TS Mean	0.0012	0.0002	0.0010
CAPM Alpha	0.0023	0.0013	0.0010
FF Alpha	0.0019	0.0014	0.0004
Carhart Alpha	0.0056	0.0055	0.0000
Panel 17: Finland			
TS Mean	0.0089	0.0067	0.0022
CAPM Alpha	0.0044	0.0024	0.0020
FF Alpha	0.0045	0.0010	0.0035
Carhart Alpha	0.0049	0.0006	0.0044
Panel 18: Austria			
TS Mean	0.0076	0.0128	-0.0052
CAPM Alpha	0.0004	0.0043	-0.0038
FF Alpha	0.0004	0.0038	-0.0035
Carhart Alpha	0.0004	0.0050	-0.0046
Panel 19: Denmark			
TS Mean	0.0106	0.0097	0.0009
CAPM Alpha	0.0062*	0.0055	0.0007
FF Alpha	0.0027	0.0042	-0.0015
Carhart Alpha	0.0031	0.0039	-0.0009
Panel 20: Greece			
TS Mean	-0.0029	-0.0073	0.0044
CAPM Alpha	-0.0082	-0.0123**	0.0040
FF Alpha	-0.0117**	-0.0188***	0.0071*
Carhart Alpha	-0.0081	-0.0145**	0.0064

Part III

Curriculum Vitae

Curriculum Vitae

Dominic Burkhardt

Personal Details

Nationality: Swiss

Date of birth: September 28, 1979

Education

Sep. 2008- **Feb. 2015**	**Ph.D. program in Banking and Finance** at the Swiss Finance Institute and the Department of Banking and Finance at the University of Zürich. Title of dissertation: *Three Essays in Asset Pricing* Supervisor: Prof. Dr. Henrik Hasseltoft Committee: Prof. Dr. Henrik Hasseltoft, Prof. Dr. Thorsten Hens
Oct. 2000- **Apr. 2008**	**M.A. in Economics (with major in Financial Economics)** at the Faculty of Business, Economics and Informatics of the University of Zürich. Thesis: *Der Forward Rate Bias in ökonomischen Zinsstrukturmodellen* Term Paper: *Implizite Volatilität als Forecast der realisierten Volatilität*
Aug. 1994- **Jan. 1999**	**Gymnasium** at Kantonsschule Enge, Zürich. Matura Type E (Economics)